Economic Cost of HIV/AIDS in India: Integrating Mental Health in Welfare Evaluation

Sanghamitra Das
Abhiroop Mukhopadhyay
Tridip Ray

Indian Statistical Institute, New Delhi

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Abstract: Using primary household data we estimate family utility function parameters that measure the relative importance of consumption, schooling of children and health (both physical and mental) and find that mental health is far more important than consumption or children’s schooling in determining household utility. We then estimate the monetary equivalent of the welfare loss at the all India level we due to the only 0.36% prevalence of HIV/AIDS is a staggering 2000 (50) billion rupees ($) per year, which exceeds the annual health expenditure of the country in 2004 and 7% of its GDP! This huge magnitude is not surprising as it includes private valuation of one's own life as well as the cost of stigma for being HIV positive. In addition, the annual loss from external transfers (through debt, dissavings and social insurance) account for 2.5% of annual health expenditure and 0.12% of GDP.

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1. Introduction

In this paper we use primary household data to estimate the economic cost of the HIV/AIDS epidemic in India by calculating directly the cost of the disease at the individual/family level for the people currently living with HIV/AIDS. In the process we offer a methodology to integrate mental health in welfare evaluation by allowing for proper substitution possibilities in the family preferences.

HIV/AIDS is gradually taking the shape of an epidemic in India and is of serious concern both locally and globally. According to the latest available estimates, there are currently about 2.5 million people living with HIV or AIDS in India, corresponding to an HIV prevalence rate of 0.36 percent for the population of ages 15-49 (IIPS, 2007). Although general HIV prevalence in India is low, there are factors that make India’s HIV/AIDS epidemic unique including the size and complexity of India’s population.

We are motivated to estimate the economic cost ‘directly’ using household data (as opposed to the ‘indirect’ measures working through the reduction in GDP or its growth rate followed by most of the researchers) due to the following reasons. While there is no question that the individuals and families of individuals infected by HIV get devastated in terms of the sickness, loss of income, children’s upbringing, early deaths, and so on, but surprisingly, estimates of the economic costs working through the indirect measures are quite modest. Most of the studies projecting the impact of HIV/AIDS on growth rate of per capita GDP use some version of the neoclassical growth model and typically estimate declines of 0.5% to 1.5% even for the worst-affected countries with more than 20% HIV prevalence rates. The key reason for these low estimates is that the increased labour productivity resulting from HIV/AIDS-induced increase in mortality reduces the population pressure on existing resources and goes a long way in offsetting all the negative effects of the disease.

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2 Also reported by UNAIDS at http://www.unaids.org.in/new/displaymore.asp?Gr=&chkey=&subitemkey=669&itemid=466&subchnm=&subchkey=0&chname=Events the HIV prevalence rate in India is only 0.36%.

3 For example, some states, and even districts, are larger than many African countries. Of the two types of HIV virus – a slow-progressing one and a fast progressing one that kills within 5 years without any anti-retroviral therapy – the latter type of virus is the predominant one in India. This coupled with the fact that India is a predominantly poor country with low levels of nutrition and a tropical country with higher exposure to various types of bacteria and viruses, including that of tuberculosis, have deadly implications for the infected.

(2005) stretched the above logic as far as to project even higher living standards of the surviving future generations of South Africa as “The Gift of the Dying” from the current generation with HIV/AIDS. To the above logic he added the decline of fertility associated with the HIV epidemic and, using South African data, estimated that the positive effects of lower population growth on real wages would be strong enough to more than offset even the most pessimistic forecasts of human capital losses due to HIV/AIDS. A similar logic is relevant for a labour surplus country like India and we do not expect to find much of an impact by taking the indirect approach working through the reduction in GDP growth rate of a booming economy.

A growing body of relatively recent literature (see, for example, Ferreira and Pessoa, 2003; Bell, Devarajan and Gersbach, 2004, 2006; Corrigan, Gloom and Mendez, 2004, 2005; McDonald and Roberts, 2006) emphasizes the transmission of human capital across generations and concludes that by disrupting the mechanism that drives the process of the transmission of knowledge and abilities from one generation to the next, the AIDS epidemic will result in a substantial slowdown of economic growth. Part of the analysis relies on the dynamic implication of the mechanism that AIDS lowers investment in human capital of children since “… the expected pay-off (from this investment) depends on the level of premature mortality among the children when they attain adulthood” (Bell, Devarajan and Gersbach, 2006, page 59; our italics). This mechanism may be applicable for countries like South Africa and Kenya where the HIV/AIDS prevalence rate has reached 20% and 25% respectively, but is not quite relevant for India with a prevalence rate of just 0.9% where there are many other compelling reasons for not sending the children to schools.

No matter what the magnitude of the aggregate effect is, we cannot deny the fact that the more than five million Indians currently living with HIV/AIDS are severely affected both at the individual and family levels. This paper determines the nature and scope of these effects and estimates the overall welfare loss from the disease at the individual/family level.5

Next, consider why we are interested in integrating mental health in this welfare evaluation. Counsellors and doctors working with HIV patients in India are unanimous in their opinion that of all types of effects of HIV that they observe what strikes them the most is the psychological cost of the patients and their families. The medical science literature has long appreciated this aspect of terminal illnesses (see, for example, Emanuel et al, 2000;

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5 We are aware of only two papers – Bell (2005) and Crafts and Haacker (2004) – that use some version of the principle of willingness to pay to calculate the direct cost of the disease. We compare our work with them in section 9.
Grunfeld et al, 2004 for some recent work). In social sciences, this is related to an emerging body of literature on happiness and mental well-being (see, among others, Easterlin, 1974, 2003; Blanchflower and Oswald, 2004, 2007; Clark and Oswald, 1997; Frey and Stulzer, 2002; Gilbert, 2006; Graham, 2007; Helliwell, 2006; Kahneman et al, 2006; Layard, 2005). The mental well-being research has proven to be well-suited in situations when revealed preferences provide limited information such as welfare effects of unemployment, divorce, smoking, drug abuse and so on. This approach can suitably be used to evaluate effects of HIV/AIDS with significant fear of early death and stigma. While researchers have worked in painstaking details to investigate the determinants of happiness and mental well-being (see, for example, Andres, 2004; Blanchflower and Oswald, 2004, 2007; Case and Deaton, 2006; Helliwell, 2006), very little research has been done to quantify the value of mental health.\(^6\) Given the importance of the psychological costs, the HIV experience in India gives us this unique opportunity to integrate mental health in welfare evaluation by allowing for proper substitution possibilities in the family preferences and to quantify its significance in welfare loss of the family.

For welfare evaluation, we use the principle of willingness to pay (captured in terms of compensating variation) by comparing the utility function estimates of the HIV and non-HIV families. To this end we collect data on 371 families affected by HIV (HIV families) and 479 families not affected by HIV (NON HIV families) from four different regions of India covering both the low and high HIV prevalence states.\(^7\)

We estimate family utility function parameters that measure the relative importance of consumption, schooling of children and mental health, which in turn depends on current and expected future health as well as HIV status in the family. Our estimates reveal that families’ weight on mental health far exceeds that on consumption or on their children’s schooling. Hence our estimates confirm the doctors’ and counsellors’ observation that the loss of welfare from HIV infection is driven by the loss of mental health.

In this context, let us briefly review the literature that has used household data to find a considerable impact of HIV/AIDS through income, consumption and children’s education. Booysen and Bachmann (2002) find that the fall in per capita income in HIV households in

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\(^6\) Blanchflower and Oswald (2004) is the only work we are aware of that has used the coefficients of subjective well-being equation to estimate welfare losses from incidents like divorce or unemployment. We compare our work with Blanchflower and Oswald (2004) in section 9.

\(^7\) This approach, though it requires more data to be collected, has the distinct advantage of not relying on recall data of infected families before infection, which we found to be quite unreliable. For example, in most cases, patients do not know when they were infected.
South Africa is 40 to 50% while the fall in per capita food expenditure is 20 to 30%. In Indonesia, Gertler et al. (2003) find that death of a prime age male is associated with a 27% reduction in mean per capita household consumption. Many studies have reported negative impact of HIV/AIDS on children’s schooling. Deininger et al. (2003) show that foster children were at a distinct disadvantage in both primary and secondary school attendance before introduction of universal primary education. Gertler et al. (2003) find that orphans are less likely to start school and more likely to drop out. Yamano and Jayne (2005) and Evans and Miguel (2005) find the negative impact of adult mortality on school attendance of children to be more severe in poor households.

This paper has three unique features. First is the Indian household dataset that has detailed information on the surveyed families. Second is our approach of evaluation of the welfare loss of HIV infected families directly in terms of compensating variation. Third is the quantification of mental health in welfare evaluation allowing for proper substitution possibilities in family preferences.

The paper is organized as follows. Section 2 discusses the data while section 3 discusses the nature of the effects observed in the data that motivate the model laid out in section 4. Section 5 presents the estimation procedure and the estimation results are presented in section 6. Section 7 discusses the measurement of welfare loss. Some robustness checks are carried out in section 8. Section 9 discusses the contribution of this paper and section 10 concludes.

2. Data

Understanding the impact of HIV on families requires information from families themselves, which is a formidable task due to the confidential nature of HIV infection. Since we were not certain about the channels of impact in India and did not want to presume what had been found for other countries, we collected information on a wide range of issues so that the data would suggest to us what the various channels of impact of the disease were.

Due to the sensitive nature of the disease and the fear of stigma, we felt that we could not succeed if we just carried out a random sample or sent out forms to doctors and NGOs all across the country. The responses, if any, would most likely be endogenous. So our approach was to use exogenous sampling, one that is not correlated with HIV/AIDS incidence, so that usual econometric methods are applicable with minor modifications (such
as the use of weights). We also wanted a sample that was representative of India. The following paragraphs describe how we took our sampling decisions keeping the overall distribution of HIV patients in mind.

Since an extremely small proportion of HIV patients in India get direct support from NGOs such as YRG care in Tamil Nadu where the HIV families live in an HIV community, we did not want to survey such families, which would have been relatively easy. Instead, we wanted to get in touch with the vast majority of families who continue to stay in the general community after the infection. Most NGOs working on HIV/AIDS are not able to provide financial help to the families themselves, but they help by educating them about the disease and by obtaining available help through public resources.

In order to ensure the necessary trust of patients, we expected that only doctors who knew us (including some of our field surveyors who had worked with HIV patients earlier) personally would agree to the surveying of their patients and the latter would trust our word of confidentiality. Hence we started with our physicians network in New Delhi, who referred us to other doctors/NGOs in various parts of the country. We followed up these contacts and ended up with data from some of the high prevalence states (Tamil Nadu, Andhra Pradesh and Maharashtra) as well as some of the low prevalence states (Delhi, Uttar Pradesh and Orissa). The number of states chosen and the sample size were constrained by a one year time limit imposed by our funders.\(^8\)

Even though this sample is not random, it is not a result of endogenous sampling either. The criterion on which our sampling was done is uncorrelated to the nature of HIV/AIDS infection. Hence standard econometric methodology is valid.\(^9\) Our results should be interpreted as the effects of HIV/AIDS conditional on the distribution of exogenous characteristics such as age, sex, education and occupation. Since this is not a study on predicting the prevalence rate in India, our sampling procedure is not biased for the purpose of this study. In our prediction of effects for the entire country we have used appropriate

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8 The doctors/NGOs explained the motives of our study to their patients but the choice to be surveyed was ultimately left to individual patients. Almost all of them agreed to be surveyed. Consent forms were signed by all. But the identities of patients surveyed through the NGOs are known to the NGOs only. Patients of doctors were mainly surveyed at the hospital or clinic of the doctors. We do have identifying information for most but these surveys are physically with us and such information is separated from the data in order to maintain current and future confidentiality.

9 We may be missing some urban rich patients who go to private doctors and are reluctant to surveys. But this criticism is equally valid to the profile of patients collected by the official National AIDS Control Organisation (NACO).
weights using the official National AIDS Control Organisation (NACO) figures to account for over-sampling of HIV patients.

In our analysis, we look at the effect of HIV on the infected adult, his/her spouse (if living) and his/her children (if present). We define this unit as “family”. This is different from a household as there may be members other than the above individuals in cohabitation, for example, sharing the same kitchen. The choice of such a unit of analysis is again dictated by the confidential nature of the disease wherein one-fourth of the patients did not disclose their status to the rest of the household excluding the spouse.

Our sample consists of 371 families where there is at least one member infected by HIV (HIV families). We have also collected data from 479 families where there is no reported incidence of HIV (NON HIV families). The selection of NON HIV families was based on geographic proximity (same village or same residential cluster in a town) and economic similarity (based on similar kind of residence) to the surveyed HIV families.

The total number of HIV affected individuals in our sample is 497, of which 58% are male and 42% (209) are female. Figure 1 reports the age distribution of HIV patients. The mean age is 33 and the sample covers reasonably well the age group where HIV prevalence is the highest in Indian population.

Moreover, our sample contains diversity in terms of how long ago HIV was detected in a person. Figure 2 shows the distribution of patients in terms of the length of time since detection. It varies from less than a month to 7 years, thus spanning a fairly long period of time to observe the effects of the disease.

Table 1 shows the various kinds of family structures in our data. Our sample includes “Currently Married” families: where both adults are alive, “Never Married” families: unmarried males or females and “Ever Married” families: widows, widowers, separated or divorced. The presence of higher proportion of ever married families among HIV families is in most cases a consequence of death of an adult due to HIV/AIDS.\(^{10}\)

In 54% of the Currently Married families, both adults have HIV infection, while in 42% of them only the male adult is infected. Of the never married HIV “families” 84% are male while 76% of the ever married families are female.\(^{11}\)

\(^{10}\) While in many cases widows do not list AIDS as the reason for death of spouse, they mention diseases like TB, which make it likely that the spouse did suffer from HIV but was not detected.

\(^{11}\) A one-member family is “male” or “female” depending on the sex of the only adult member.
There are 1418 children in our data of which 1189 are less than 18 years of age. The average number of such children per HIV family (among families who have children) is 2.16, while the average number of such children per NON HIV family is 2.22. We assume that parents make decisions for children who are less than or equal to 18 years of age and children older than 18 are able to take decisions for themselves.\textsuperscript{12} For obvious reasons, schooling decisions are considered for children in the age group 6 to 18. The total number of such children in the sample is 892. Among HIV families the average number of such children is 1.9 while the corresponding number for NON HIV families is 2.1.

The average years of schooling among HIV infected males in our sample is 10.3 years while the average years of schooling among males in the control group is 8.4 years. The corresponding figures for females are 5.46 years and 5.2 years, respectively. While the PLWHA (People Living with HIV/AIDS) in our sample are not very educated, it is interesting to note that the level of education among males is higher than that in the control group.

Table 2 reports the occupation profile of HIV persons before they were detected with HIV. A look at the occupation profile of HIV males shows that most of them were industrial factory workers.\textsuperscript{13} We highlight this here because of the increasing concern of HIV spread among migrant labourers. Most of the industrial factory workers and Auto/ Car/ Bus drivers belong to this group. Among HIV infected females in our sample, about 60% are housewives, while the next big group is agricultural labourers. These are usually occupations of spouses of migrant workers.\textsuperscript{14} This suggests one way the HIV virus is making an inroad into the rural economy: through migrant workers infecting their spouses when they visit home.

\textsuperscript{12} The rationale for such an assumption is that in this latter age group 45\% of the children live away from the family (for both HIV and NON HIV families). Hence it is not feasible to obtain all information on them. However, if they send money to the family, it is treated as transfers.

\textsuperscript{13} We do not report current occupation data here as that is endogenous. While we do not use recall data for most of our analysis as it is unreliable, it is unlikely that the occupation before HIV detection will be misreported. Hence we use this part of the recall data.

\textsuperscript{14} The category “other occupations” includes a whole variety of occupations.
3. Impacts

Let us now move on to the variables that reveal effects of HIV on families. The conclusions of the following sub-sections are a motivation for our model and our econometric procedure.

3.1. Physical Health

The survey asked a number of questions on the occurrence of common symptoms of infection (fever, diarrhoea, cough and cold, loss of appetite, general body ache, and headache). Moreover questions were asked regarding some diseases and symptoms that are seen more often in HIV patients than NON HIV such as tuberculosis, knots, oral ulcers, and genital ulcers. The reference period for the above symptoms was the last three months.15

Given the symptoms, we took the help of an expert in HIV treatment at a government Anti Retro-viral Treatment (ART) clinic, who assigned a numerical index based on the symptoms for all the HIV and NON HIV respondents. We use this index as a measure of morbidity. The index ranges from 1 to 11 with 11 being the healthiest and 1 being of the worst health.

Table 3 summarizes this health index by gender and HIV status.

A $t$-test of equality of means suggests that the health index based on morbidity is significantly lower for HIV individuals as compared to that of NON HIV individuals ($t$ value of 16.5; significant at 1% under the alternative hypothesis that NON HIV health index is higher). In our sample, the morbidity of HIV males is significantly higher than that of HIV females (with a $t$ value of 28: rejection of equality of mean against the alternative of health index of females higher than that of males), reflecting that usually husbands are infected earlier.

Since our analysis is at the family level, we construct the average health of a family by taking the mean over the health of existing adults in the family. This controls for different number of adults in families. Thus, as expected, HIV families have lower physical health as compared to NON HIV families.

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15 We are aware that health experts are in favour of much shorter reference periods, for example last 15 days. We extended the period to pick up the fact that PLWHA do, on the average, have higher morbidity but go through periods of ‘normal’ health and so we wanted a long enough period to pick up this difference.
3.2. *Mental Health*

We construct an index of mental health based on self-reported occurrence of depression related feelings of the respondent and his/her spouse (for married respondents). Questions on feelings were asked using the questions in Case and Deaton (2006). The following statements were made and the respondents were asked if in the last 15 days the occurrence of the feeling captured by each statement was “Hardly ever”, “Sometimes”, “Most of the time” or “Never”.

- I felt that I could not stop feeling miserable, even with the help of my family and friends;
- I felt depressed;
- I felt sad;
- I cried a lot;
- I did not feel like eating; my appetite was poor;
- I felt everything I did was an effort;
- My sleep was restless.

The ranking of mental health was made explicit by giving a number to each answer: “Never” was given 4 points, “Hardly ever” 3 points, “Sometimes” 2 points and “Most of the time” 1 point. Using these values, we construct a mental health index ($IMH_1$): minimum of the points across all questions answered by the respondent and, where present, by his/her spouse. This is the Rawlsian “maximin” criterion and is characterized by some basic axioms regarding aggregation (Sen, 1986). It does not rely on cardinality (as an average would have). But it assumes comparability of this ordinal measure across different subjects. It also gives equal importance to all questions. To check if choice of index makes a big difference, we also consider another index which is similar in its Rawlsian flavour but uses responses to only one question: “I felt depressed” ($IMH_2$).

Both these indices are ordinal. Hence a higher value of the index implies higher mental health. Table 4 summarizes the distribution. It is clear that the distribution of $IMH_1$ as well as $IMH_2$ for NON HIV families always dominates the distribution for HIV families. Thus NON HIV families are mentally better off whichever index one considers.

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16 We use the questionnaire in Case and Deaton (2006) as it was already tested on a sample of 1000 households in 100 villages in Udaipur district in India. The same sample has also been used by Banerjee, Deaton and Duflo (2004).
3.3. Labour Supply

Table 5 shows the occupation transitions of HIV patients. These are based on current occupations of HIV patients and their occupations before HIV detection (BHD). As can be seen from Table 5, for an employed HIV male, the probability of becoming unemployed upon being detected is 0.2. Moreover, the current unemployment rate of males, 13.13% is much higher than the BHD value of 5% (Table 2). But, interestingly, in case of women patients, 21 out of the 132, who did not work before HIV detection, start working – among them 13 are widows.

A large part of male unemployment could be because of poor physical health. Table 6 shows that positive labour supply outside (denoted by \( l \)) by males is associated with lower morbidity. This is not equally true of females as many females are housewives and they chose not to provide labour outside home even when they have lower morbidity.

We have already noted that health and gender may have a role to play for whether PLWHA are employed. But is labour supply a choice? Since our sample captures a rather poorly educated section of Indian society, it is important to ask if individuals actually choose their labour supply based on wages. A positive correlation between wages and labour supply may be misleading. It may well be the case that while individuals may want to supply as much labour as they can, education levels sort them into various occupations and a well-paying job comes with more certain employment and therefore more days of work. Thus in any regression specification one needs to control for the occupation of the respondents.

It is unreasonable to assume that in mainstream Indian society not working is a choice for males. Only 6% of NON HIV males (who are less health constrained) do not work.\(^{17}\) For those who are working, we regress the number of days of work in a week on the wage per day, occupation, education, health status, a dummy for whether the male is HIV and the number of members in a family. We find that only the occupation dummies are significant. This suggests that, conditional on being able to work, one cannot choose the number of days of work. This is consistent with the common notion of India being a labour surplus economy. Hence, for the rest of the analysis, we take the labour days of males as exogenous, conditional on being able to work.

\(^{17}\) It is virtually impossible to check whether wages affect the choice of not working. For those who are not working, one needs to impute a wage. A good proxy for wages is the education level.
About 70% of the all sampled women do not work currently. Most women who do not work do so because they are housewives. The decision to work for women may be endogenous due to death of spouse or increased expenditure due to HIV. In our data 21 women from HIV families start working after HIV detection, 13 of them widows, showing a change in the labour-leisure trade-off after HIV detection, particularly after widowhood. Unfortunately, any empirical analysis is infeasible with such a small sample to identify the effect. We are therefore forced to ignore this effect, treating female labour supply as exogenous too.

3.4. Effect on Children’s Education

Does HIV in families affect school attendance? We measure the effect in terms of the proportion of children in the age group 6 to 18 in a family (multiplied by the schooling expenditure on them to adjust for the quality of schooling) attending school. Table 7 shows the possible effect of HIV/AIDS on children’s education. It seems that while both parents are alive there is no big impact of HIV on school attendance. However it is clear from the data on one-parent families that there are significant effects on school attendance when one parent is dead. This reflects the long run adverse impact of HIV on human capital development.

3.5. Income, Expenditure and External Funding

Since we treat labour supply as exogenous conditional on being able to work, families do not choose how much labour income they will get. Thus incomes depend on their education, occupation and their physical health (morbidity). Apart from labour income, in some cases, there are rental incomes, which we add to calculate total income of a family. Table 8 reports the effect of HIV on income and expenditures across various family types.

Per capita incomes of the HIV and NON HIV families are not significantly different from each other. Widow families have the lowest income. Since widowhood is an advanced stage of how HIV affects a family, it can be seen that the fall in income traces out how incomes will be affected in the long run for a family. In comparing married HIV families and widow families, it is interesting to note that while income falls, per capita consumption does not. The main reason for this is the rather large amounts of net external funding (transfers from the extended family, loss of savings, sale of assets and debts). Unfortunately we do not
know the timing of these funds so that we cannot examine the dynamic impacts of this external funding.\textsuperscript{18} For this analysis we take such funding to be exogenous.

4. The Model

In order to estimate the economic impact of the HIV/AIDS epidemic in India, we develop a simple model based on our initial considerations that can be quantified with our sample discussed in the previous section. The unit of analysis is the family consisting of the man, the woman, and the children. We assume that all the economic decisions of the family, including the decisions for the children, are taken by the adult members. When a child becomes adult, he/she starts his/her own family, and the decision problem of that new family is not our concern in this model.

Consider first the preferences of the family. As argued in the data section, labour supply is not a choice for the families surveyed in our sample. Hence we abstract away from the preference for leisure in the family utility functions. Preferences are of course defined over the family’s per capita consumption expenditure, \( c \), and over an index of children’s education, \( CE \), taking all the school-age children of the family into account. Further, and, for the context of this study, most importantly, mental health of the family (\( M \)) and its physical health (\( H \)) are also allowed to influence a family’s utility.

Consider mental and physical health first. One important component of the cost of HIV/AIDS that we would like to focus on is the impact working through the mental health of a family. Mental health picks up many different effects in a compact form. The HIV infected member will of course feel miserable – shocked (after being diagnosed HIV positive), depressed, worried about future health, income and children’s upbringing, and possible early death. The spouse, in addition, might feel cheated, embarrassed and worried about the future. And the entire family might suffer from the stigma from friends and neighbours.

At the same time, HIV/AIDS does have an obvious impact on the state of physical health. In our analysis below, we treat the current state of health as predetermined.\textsuperscript{19} However, for a given state of health, medical expenditures \( md \) can be expected to have a

\textsuperscript{18} For example, initially the family may brave the disaster by drawing upon its past savings, selling assets or borrowing from the extended family. But, as time passes by, these sources of external funding gradually dry out leaving the family in a precarious condition.

\textsuperscript{19} While medical expenditures can be considered to improve health, poor physical health triggers higher medical expenditures. Consequently, medical expenditure and current physical health are negatively correlated in our sample. Due to the cross-section nature of our data we are not able to disentangle these two effects and therefore treat the current state of health as predetermined.
positive impact over expected future health, $H^f$, with $H^f = H^f(H,md)$. But since $H^f$ is not observable, we postulate that the family’s preference for expected future health is reflected in its mental health: a significant component of mental health consists of the worry about future health and the family can take some relief by spending money on medicines ($md$). That is, we postulate that, among other things, $H^f$ is a determinant of mental health.

As for the possible other determinants of mental health, following the emerging literature on mental health and subjective well-being and considering the specific case of HIV and the existence of extended family structure in India, we consider a host of factors like wealth, employment status, age, sex, HIV dummy, extended family dummy, and so on. Clubbing all these variables as the vector $X^{20}$ and incorporating $H^f(H,md)$, we specify the following underlying relationship determining the mental health of a family:

$$M = \delta_0 + \delta_1 \cdot md + \delta_2 \cdot H + \lambda \cdot X.$$  

(1)

Next consider children’s education. In line with the literature on transmission of human capital, we also take a closer look at the process of human capital formation. Since we only consider the current allocation problem of the family, and there is no production in the model being affected by ‘human capital’, to capture the impact of HIV on human capital formation we postulate that the family cares for its children’s education. Let $CE$ denote the index for children’s education taking all the school-going age children of the family into account, and the family’s preference is defined over this index $CE$. We describe below how we come up with an expression for $CE$ that is consistent with our sample.\textsuperscript{21}

Ideally an index of human capital accumulation by each child, $E$, should depend on the fraction of time the child spends studying ($e \in [0,1]$) and the quality of schooling ($\sigma$), that is, $E = E(e,\sigma)$, and a choice of $e$ should be allowed by taking into account the opportunity cost of a child’s time. We considered the opportunity cost of educating children in the form of lost income from working and allowing for a choice of $e \in [0,1]$. But only 52 out of a total of 892 children (ages 6-18) in our sample are child labourers and hence this cost is unimportant. Further, in our sample of school-age children, 47.5% study for 6 hours, 27% study for 8 hours and 12% study for 5 hours and these seem to depend on class and state of

\textsuperscript{20} See equation (9) below for the complete list of explanatory variables clubbed under $X$.

\textsuperscript{21} We would like to thank Clive Bell for his suggestions that have clarified our exposition of the family’s preference for children’s education.
residence. Very little extra studying is done, which is not surprising for the education levels of the families in our sample. The lumping of studying hours implies that they are more or less synonymous with school hours. When we regress studying hours (for those attending school) on wealth, age, gender of the child and state dummies, only age and state dummies are significant. Thus school hours can be taken as exogenous. Hence in our specification, $e = \bar{e}$, that is, $E(e, \sigma) = E(\bar{e}, \sigma) \equiv E(\sigma)$. We postulate that $E(\sigma) = \sigma$. Since $E$ is the index of human capital accumulation for each child, it needs to be weighted by the proportion of school-going children ($P_S$) in order to come up with an index for children’s education for the entire family. Finally, we propose that quality of schooling ($\sigma$) could be well-proxied by per capita schooling expenditure ($SC$). Thus, the expression for $CE$ becomes: $CE = P_S \cdot SC$.

We observe that a significant proportion of families in our sample (48%) do not have any children. Hence we assume that these families do not put any weight on children’s education in their family utility function. Considering the discussion above, we postulate the following utility functions for the two broad family types:

Families with school-age children: $u = \alpha \log c + \beta \log(1 + M) + \gamma \log(1 + SC \cdot P_S)$, \(2\)

Families without school-age children: $u = \alpha \log c + \beta \log(1 + M)$.

Next consider the budget constraint faced by the family. Since we treat labour supply as exogenous, labour income of the family is given. This labour income, coupled with incomes from other sources like rental income and net external funding (transfers from relatives, loss of savings, sale of assets and debts), give the total income of a family ($Y$).\(24\)

The family allocates this total income between consumption expenditure ($c$), medical expenditure ($md$), and schooling expenditure ($SC \cdot P_S$) (in case of families with children), that is, the budget constraints for the two types of families are given by:

---

22 Proportion seems to be the right weight rather than the total number. Multiplying with the total number has the undesirable property that it gives undue advantage to having more children. We focus on the quality of a representative child. This differs from studies that use number of children as an argument in the utility function.

23 Since $P_S$ may be zero, the number one has been added to normalize the sub-utility from children of school age to be zero when $P_S$ is zero. One is also added to $M$, which, as explained in the next section, is measured as a latent variable that can possibly be zero.

24 Note that the actual decision problem facing the family is intertemporal in nature with savings and dissavings adjusted optimally to brave the immediate disaster. This is evident from the large amounts of sales of assets, debts or loss of savings (included in net external funding) mentioned in the last section. But, given the one-shot nature of our data, we cannot address this intertemporal decision problem. Instead, we analyze the intratemporal allocation problem where $Y$ stands for total spending.
Families with children: \( N \cdot c + md + (SC \cdot P_s) \times n_s \leq Y \), \( (4) \)

Families without children: \( N \cdot c + md \leq Y \).

Here \( N \) is the family size and \( n_s \) denotes the total number of children in the school-going age (between 6 and 18 years).

**The Decision Problem of Families with Children:**

Maximize \( \alpha \log c + \beta \log(1 + M) + \gamma \log(1 + SC \cdot P_s) \) subject to (1) and (4).

The first-order conditions of this optimization problem give the following three equations which we take to the data for estimation.

\[
N \cdot c = \left( \frac{\alpha}{\alpha + \beta + \gamma} \right) \left[ Y + \frac{1+Z}{\delta_1} + n_s \right], \quad (6)
\]

\[
md = \left( \frac{\beta}{\alpha + \beta + \gamma} \right) \left[ Y + \frac{1+Z}{\delta_1} + n_s \right] - \frac{1+Z}{\delta_1}, \quad (7)
\]

\[
SC \cdot P_s = \frac{1}{n_s} \left( \frac{\gamma}{\alpha + \beta + \gamma} \right) \left[ Y + \frac{1+Z}{\delta_1} + n_s \right] - 1, \quad (8)
\]

where \( Z = M - \delta_1 \cdot md \). Decision for families without children is a special case of the above.

**5. Estimation Procedure**

We estimate two different utility functions for families with school-age children and for those without them. Table A.1 in the Appendix has the summary statistics for all the variables used in our estimation. In each case we pool HIV and NON HIV families. We describe the method for the case of families with school-age children. The method for the case without such children is exactly the same except that there is no schooling decision and hence one equation will be reduced.

**5.1. Mental Health Equation**
First consider the family mental health equation. Let us elaborate on the explanatory variables clubbed under vector $X$ in equation (1). Following the emerging literature on mental health and subjective well-being (see, for example, Andres, 2004; Blanchflower and Oswald, 2004, 2007; Case and Deaton, 2006; Helliwell, 2006), we include wealth ($W$), whether any adult family member is unemployed ($D_{UNEMP}$), the average age of adult family members ($Av\_age$), the square of average age ($Av\_age^2$) and a dummy for whether there is a female member in the family ($D_{FEM}$). Also, considering the specific case of HIV, we include an HIV dummy ($D_{HIV}$) and the time span since the first detection of HIV in the family ($ts$). We allow for regional differences in mental health by defining a dummy variable for the northern states ($D_{NORTH}$) in our sample. Finally, considering the extended family structure in India and the possibility that an HIV family may get more emotional support in an extended family, we include a dummy variable, $D_{EXT}$, to denote whether a family is a part of an extended family.

Thus, the estimable family mental health equation is:

$$
M_i = \delta_0 + \delta_1 \cdot md_i + \delta_2 \cdot H_i + \delta_3 \cdot ts_i + \delta_4 \cdot ts_i^2 + \delta_5 \cdot W_i + \delta_6 \cdot D_{HIV} + \delta_7 \cdot D_{FEM} + \delta_8 \cdot D_{EXT} + \delta_9 \cdot D_{UNEMP} + \delta_{10} \cdot Av\_age^2_i + \delta_{11} \cdot Av\_age^{2i} + \delta_{12} \cdot D_{NORTH} + \omega_i.
$$

The quadratic effect of $ts$ is meant to capture possible non-linear movement of mental health after one finds out about HIV in the family such as an initial shock and then acceptance of the fact or hopelessness.

Equation (9) is a technological relationship that relates how medical expenditure, physical health and the other explanatory variables translate into mental health of the family. Thus this equation can be estimated on its own. But before we do so, we have to deal with the fact that the mental health index we constructed from our data is an ordinal measure, whereas the mental health variable in equation (9) is a continuous measure. The data and our index are reconciled by assuming that the responses of families (given by the orderings) are based on an underlying latent mental health variable $M$, given in equation (9). We further assume that the errors in equation (9) follow a normal distribution, which results in an ordered probit model. Thus we estimate parameters $\delta_0$ to $\delta_{12}$ by ordered probit.$^{25}$ Using these parameters we calculate the predicted value of $M$ for each family. We use the predicted

---

$^{25}$ This is in line with Blanchflower and Oswald (2004, 2007) who use ordered logit. The qualitative results do not change if we assume a logit specification.
value $\hat{M}$ for the rest of our empirical analysis as the (continuous) measure of mental health for each family.

5.2. Consumption, Medical Expenditure and Schooling Equations

There are three equations to estimate the underlying parameters when $SC \cdot P_s$ and $md$ are strictly positive. Define

$$\phi_1 \equiv \frac{\alpha}{\alpha + \beta + \gamma}$$

$$\phi_2 \equiv \frac{\gamma}{\alpha + \beta + \gamma}$$

and

$$\phi_3 \equiv \frac{\beta}{\alpha + \beta + \gamma}.$$

Then the estimable consumption, medical expenditure and schooling equations are:

$$N_i \cdot c_i = \phi_1 \cdot \left[ Y_i + \frac{1 + Z_i}{\delta_i} + n_{si} \right] + \varepsilon_{1i},$$

(10)

$$n_{si} \cdot (1 + SC_i \cdot P_s) = \phi_2 \cdot \left[ Y_i + \frac{1 + Z_i}{\delta_i} + n_{si} \right] + \varepsilon_{2i},$$

(11)

$$md_i = \phi_3 \cdot \left[ Y_i + \frac{1 + Z_i}{\delta_i} + n_{si} \right] - \frac{1 + Z_i}{\delta_i} + \varepsilon_{3i},$$

(12)

where $Z_i = M_i - \delta_i \cdot md_i$.

Equations (10), (11) and (12) form a seemingly unrelated system of equations (SURE) for the family. However, since the three add up to income in the budget constraint, only two of them can be used for estimation. We use equations (10) and (11). Notice that they have the same regressors. Hence system OLS is consistent and efficient and reduces down to doing OLS equation by equation.

An issue of concern using OLS equation by equation is the possibility of selection bias. In the structural model, these equations hold for positive $md$, $c$ and $SC \cdot P_s$, so we use only the observations when these conditions hold. However one can argue, a la Heckman, that these make the estimates inconsistent. To check for that we ran the models on the full sample with Heckman corrections but since $md$ and $SC \cdot P_s$ are zero for a very small proportion of our sample (about 10% for both), the estimates were almost identical. Therefore the OLS parameters are consistent and efficient.
The OLS regressions yield $\hat{\phi}_1$ and $\hat{\phi}_2$, whereas $\hat{\phi}_3$ is derived from the restriction: $\hat{\phi}_1 + \hat{\phi}_2 + \hat{\phi}_3 = 1$. For the sample without school-age children we first estimate the mental health “technology” equation. Since there is no schooling decision, we only estimate equation (10).

In all our estimation procedures, we pool the HIV and NON HIV sample and since we have over-sampled HIV families as compared to their proportion in the all-India population we use weighted least squares (and weights for probit) to correct for this possible source of bias. Our weighting procedure is sincere to our sampling procedure. While sampling, we sampled a family when we found out that there was a HIV infected person in the family. We did not explicitly look to sample HIV men or women. Neither did we attempt to sample a certain kind of family (male infected or female infected or both infected). Hence we will assume that conditional on finding a HIV person, his/her family structure is representative. Thus our weighting procedure takes into account the probability of finding the main respondent who is HIV (irrespective of whether the spouse is HIV). In other words, the weight given to a family is the weight of male HIV if the main respondent is male and vice versa if the main respondent is female HIV. It turns out our sampling proportions of each gender are almost similar to the population proportions given by NACO. Since we over-sampled HIV respondents, we need to put a smaller weight on them to be truly representative. As an example,

Weight of a family with main respondent male = \frac{\text{Proportion of HIV males in population}}{\text{Proportion of HIV males in sample}}.

Thus, as can be seen in Table 9, when we pool the data, any family with a HIV respondent gets a very low weight, while NON HIV families get much higher weight. Notice that since we have very few female respondents for NON HIV families, they have to be weighted the most.

Finally, all standard errors in the following analysis are robust.
6. Estimation Results

First let us look at the determinants of mental health. Table A.2 in the Appendix reports the ordered probit estimates with the full set of possible explanatory variables as specified in equation (9). Since only a subset of variables is significant, and we would like to use the predicted value $\hat{M}$ for the estimation of preference parameters, we conduct a joint significance of a subset of variables that are insignificant in themselves (Table A.3 in the Appendix) and, based on this Wald test, we drop the insignificant variables and then re-estimate equation (9) with only the significant variables. The results for both measures of mental health, $IMH_1$ and $IMH_2$, are reported in Table 10.

Since these are not the marginal effects, we only discuss the signs of the coefficients and not the magnitudes. For both measures, better current physical health leads to better mental health. Controlling for current physical health, the higher the medical expenditure the higher is the mental health. This is an important result for our model. We contend that, controlling for current physical health, people who spend more money on medical expenditure, do so to affect their expected future health. The significant and large coefficient on $D_{HIV}$ suggests that HIV infection affects mental health negatively.

The effects of other variables are specific to the measure of mental health considered. With $IMH_2$, we get the “U” shaped relation between mental health and age, as well documented in the recent well-being literature. The coefficients of time span variable suggests that, controlling for physical health, the measure based on self reported depression gets better as more time passes and the non-linearity is not evident. Wealth affects $IMH_1$ positively. Belonging to an extended family increases mental health ($IMH_1$), as expected. Presence of a female member lowers the mental health ($IMH_2$) of the family. The basic flavour of our results is not too different if we assume a logistic distribution instead of normal distribution for the error term.

As mentioned earlier, we now use the ordered probit estimates to convert the ordinal ranking in our mental health measure to a continuous quantitative measure given by the latent variable underlying the ordered probit model. We use this continuous measure in our empirical analysis below including the estimation of equations (10 – 12). For the remaining part of the paper, we report the results using $IMH_1$ as it uses all our questions reflecting depression (results are similar with $IMH_2$).
Table 11 reports the estimates of the parameters of the consumption and schooling equations. The estimate of parameter relating to mental health is computed by subtracting the sum of the reported estimates from one. The relative magnitudes confirm the observation made by the doctors and HIV counsellors: mental health (which in turn depends on current and expected future physical health) in the family utility function is much more important than consumption or children’s education. Children’s education is the least important.

To get a concrete measure of welfare loss due to HIV we use these utility function estimates to obtain a monetary equivalent value of the loss to each family in the next section.

7. Measurement of Welfare Loss

The welfare loss of the HIV/AIDS epidemic at the family level is calculated by comparing the indirect utility functions of the HIV infected families with the NON HIV families. Let $S$ stand for the vector of the exogenous variables in the model:

$$S = (Y, H, N, n_S, W, ts, D_{HIV}, D_{FEM}, D_{EXT}, Av_{age}),$$

and $\tau$ denote the (hypothetical) transfer that a family receives from outside. Then the family’s indirect utility function with this hypothetical transfer $\tau$, $V(S | \tau)$, is defined as

$$V(S | \tau) = \left\{ \begin{array}{l}
\text{Maximize } \alpha \log c + \beta \log(1 + M) + \gamma \log(1 + SC \cdot P_s) \\
\text{s.t. } N \cdot c + md + (SC \cdot P_s \times n_S) \leq Y + \tau, \text{ and } \\
M = \delta_o + \delta_1 \cdot md + \delta_2 \cdot H + \lambda \cdot X
\end{array} \right.$$

Consider any two families – family $i$ with $S_i$, and family $j$ with $S_j$. If family $i$ is the reference family, then the amount of compensating transfer (CV) $\tau^{ij}$ needed to bring the family $j$ up to the same (indirect) utility level as the reference family $i$ is defined by:

$$V(S_j | \tau^{ij}) = V(S_i | 0).$$

When the reference family $i$ is an average NON-HIV family and family $j$ is an average HIV family, then $\tau^{ij}$ measures the monetary equivalent of welfare loss from HIV/AIDS to an average HIV family.

Given the Cobb-Douglas utility specification, solving the expression for $\tau^{ij}$ for families with school-age children yields:
\[
\tau^{ij} = \left[ Y^i + \frac{1 + Z^i}{\delta^i_1} + n^i_s \right] \cdot \left[ \frac{N^j}{N^i} \right]^{\alpha + \beta + \gamma} \cdot \left[ \frac{n^j_s}{n^i_s} \right]^{\gamma} - \left[ Y^j + \frac{1 + Z^j}{\delta^j_1} + n^j_s \right].
\]  

(13a)

For families without school-age children:

\[
\tau^{ij} = \left[ Y^i + \frac{1 + Z^i}{\delta^i_1} \right] \cdot \left[ \frac{N^j}{N^i} \right] - \left[ Y^j + \frac{1 + Z^j}{\delta^j_1} \right].
\]  

(13b)

7.1. Monetary Equivalent of Welfare Loss (CV)

Note that we have (using IMH_i)

\[
1 + Z = 1 + \delta_0 + \frac{\delta_2}{\delta_1} W + \frac{\delta_5}{\delta_1} D_{HIV} + \frac{\delta_8}{\delta_1} D_{EXT} + \frac{\delta_{11}}{\delta_1} \text{Av_age}^2.
\]

Now, for example, consider two families i and j such that family i has no HIV positive adult \((D_{HIV} = 0)\) whereas family j has at least one HIV positive adult member \((D_{HIV} = 1)\), and the two families are identical otherwise.\(^{26}\) Then (13) implies:

\[
\tau^{ij} = -\frac{\delta_6}{\delta_1} = 66,039,
\]

that is, the monetary equivalent of the welfare loss to an HIV family is Rs. 66,039 per month.

Similarly, consider two families i and j differing only in physical health (morbidity), that is, \(H_i \neq H_j\), but identical otherwise. Then (13) implies:

\[
\frac{\partial \tau^{ij}}{\partial (H_i - H_j)} = \frac{\delta_2}{\delta_1} = 13,652,
\]

implying that “other things remaining the same”, (money) value of one unit of physical health improvement to a family is Rs. 13,652 per month.

Table 12 lists all these partial effects on compensating variation using IMH_i.

7.2. Welfare Loss from HIV: the All-India Picture

Table 12 points out the partial effects on welfare loss where “other things remain the same”. But we are also interested in the total effect (at the all-India level) where other things are not necessarily the same. For this purpose we consider a married NON HIV family as the reference group because widowhood, widower-hood as well as the state of being unmarried can well be a consequence of HIV infection.

\(^{26}\) That is, \(Y_i = Y_j, H_i = H_j, N_i = N_j, n_{Sl} = n_{Sj}, W_i = W_j, t_{Si} = t_{Sj}, D_{EXTi} = D_{EXTj}, \) and \(\text{Av_age}_i = \text{Av_age}_j.\)
In order to estimate the welfare loss at the all-India level we proceed as follows. First we compute the loss to each family. For married couples with one infected member, widows, widowers and unmarried individuals, we ascribe the whole loss to the infected member. For married couples where both members are infected we split the loss equally between both members. We add all the losses up for our sample. We find the average loss per male and the average loss per female and then to estimate the cost at the all-India level we scale it up in proportion to the number of HIV males and females in India using the most recent figures on gender breakup that is available. Table 13 summarizes the all-India picture of welfare loss.

The total loss (using $IMH_1$) per month is Rs. 67,601 for a male living with HIV/AIDS and Rs. 65,120 for a female (the respective figures using $IMH_2$ is Rs. 76,986 for males and Rs. 84,272 for females). This implies that the loss to the male HIV affected population in India (using $IMH_1$) is Rs. 104.78 billion per month and that for female population is Rs. 61.86 billion per month or a total of Rs. 166.64 billion per month based on a total number of 1.55 million males and 950 thousand females living with HIV/AIDS in India (using gender proportions from UNAIDS figures). The total HIV cost per year with 0.36 percent of the population affected thus comes out at Rs. 1999.8 billion (7 percent of GDP), which is more than the annual health expenditure of Rs. 1,356 billion (2004) for all ailments in India!

Such a huge magnitude is not surprising because it reflects the private valuation of one’s life as well as the cost of stigma for being HIV positive. Blanchflower and Oswald (2004), the only work we are aware of that has tried to quantify welfare losses using subjective well-being estimates, also come up with similar large figures. They estimate that a typical individual in the US or Britain would need $100,000 per annum to compensate for the well-being loss resulting from divorce. The corresponding figure for job loss for an average male is $60,000 per annum. In the same vein, Crafts and Haacker (2004) evaluate the welfare cost of increased mortality associated with HIV/AIDS and estimate similar large figures for welfare losses: in Vietnam, with an adult HIV prevalence rate of only 0.4%, welfare loss already exceeds 2% of GDP, whereas in Botswana, with 37.3% prevalence rate, the welfare loss is around 90% of GDP.

Finally, we would like to draw attention to another source of loss to the society that occurs due to loss of savings, sale of assets, increase in debts or increase in monetary

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27 Even though the overall prevalence rate has been updated by UNAIDS, no corresponding information is available on gender composition of the HIV infected. Hence we use the same gender proportion of the infected as the last available one along with the current prevalence rate to draw our conclusions.
transfers from relatives – everything that we have clubbed under net external funding in Table 8. We treat these as losses as these funds have alternative uses and hence represent a drain of economic resources due to loss of labour income and increased medical expenditure. We calculate this loss due to transfers following the same method as outlined above with married NON HIV families as the reference group. The loss per HIV male comes to Rs. 13,584 per annum while that for the female is estimated to be Rs. 14,544 per HIV female. This amounts to Rs. 21 billion for all males and Rs. 13.8 billion for all females. The total loss from transfers is 2.6% of the total health expenditure of the country and 0.12% of GDP in 2004. These numbers are also quite large given that only 0.36% of the population is infected by HIV/AIDS.

7.3. Welfare Losses across Family Types

We observed in section 3 that the ‘widow’ families could be particularly vulnerable – they have the lowest per capita income, the highest drop-out of school-going children, and a significant change in the labour-leisure trade-off. Since we have data for various different family types, we are interested to know whether the welfare losses differ significantly across different types of families with HIV. For this purpose we regress the welfare losses (using \( IMH_1 \)) on dummy variables reflecting different family types. We use the Only Male HIV Married Families as the control group as it is the most common type of HIV family. We also regress losses due to transfers (deviations of net external funding from the level of NON-HIV Married Families) on family types.

Table 14 reports this regression result that says that the welfare loss per month is Rs. 86,217 for an average HIV family where only the male adult is infected. The loss is reduced to Rs. 67,882 for an average HIV family where only the female adult is infected, and increases to Rs. 92,284 when both adults are infected. It is important to note that the highest loss among all family types occurs to the widow HIV families, Rs. 93,360 per month. Clearly, the widow HIV families are in the most vulnerable situation and need careful attention from any policy initiative. From the last column of Table 14 it is also clear that the losses due to external funding is the highest for the unmarried females and widows.
7.4. Welfare Loss: Significance of Mental Health

In this section we delve a bit deeper into the determinants of welfare loss to highlight the significance of mental health. Table 15 reports the various disaggregates of the money equivalent expressions given in equation (13)\textsuperscript{28, 29}

From Table 15 it is clear that the differences in \( \frac{1+Z}{\delta_1} \) dwarfs the differences in \( Y \) between the HIV and NON HIV families. As a matter of fact, most HIV families have higher \( Y \) than NON HIV families. The other two variables, \( N \) and \( n_S \), do not play that big a role since

\[
\left[ \frac{N}{N'} \right]^{\alpha + \beta + \gamma} \cdot \left[ \frac{n_s}{n_s'} \right]^{\gamma} \text{ is usually close to one as neither the average family sizes nor the average number of school-age children are that different between the HIV and NON HIV families.}
\]

The estimates for \( \frac{1+Z}{\delta_1} \) come from the mental health technology (Table 10) and emphasize the role of mental health in our analysis.

In order to further understand the significance of different components in welfare loss, Table 16 reports the contribution to welfare loss coming from the differences (with the reference NON HIV married families) in some key components like physical health, wealth and HIV status. For example, the figure 16,213 in row 1 column 1 says that for the only male HIV married families, out of the welfare loss of Rs. 86,217 per month (see Table 14), Rs. 16,213 is contributed by the differences in physical health.\textsuperscript{30}

It is clear from Table 16 that the maximum contribution to welfare loss comes from the HIV dummy: the sheer fact that one family member is HIV positive hits the family the hardest. The HIV dummy of course captures, in a nutshell, all the other aspects of mental health that we could not separately quantify in the mental health estimation (Table 10) such

\textsuperscript{28} \( Y \) is different from Income in Table 8. There the per capita income does not include transfers. It is lower than \( Y \) reported in this table.

\textsuperscript{29} In Table 15 we consider only those family types that are significant in the welfare loss regression reported in Table 14.

\textsuperscript{30} The figure 16,213 is calculated (using equation (13) and the expression for \( \frac{1+Z}{\delta_1} \)) as follows:

\[
\left[ \frac{\delta_2}{\delta_1} \right] H^i \left[ \frac{N^j}{N'^i} \right]^{\alpha + \beta + \gamma} \cdot \left[ \frac{n_j}{n_j'} \right]^{\gamma} \cdot \frac{\delta_2}{\delta_1} H^j = 16,241
\]

using \( i \) for the reference NON HIV married families, \( j \) for the only male HIV married families and taking sub-sample averages for all the relevant variables – \( H, N \) and \( n_S \).

24
as worry about possible early death or social stigma. Contribution of physical health differences is the next important factor; it is particularly high for the widow families.

8. Robustness

We have carried out two robustness checks to validate our exercise: first, with respect to the choice of mental health index, and second, with respect to the choice of the utility function.

8.1. Choice of Mental Health Index

Although we have presented most of the results using $IMH_1$ (minimum of the points across all the mental health questions answered by the respondent), but, time and again, we have also compared them with $IMH_2$, the index that uses responses to only one question: “I felt depressed”. The mental health technology equation estimates somewhat differ depending on which index one uses (see Table 10). But the significance and magnitudes of the key variables like $md$, $H$ and $D_{HIV}$ are not very different so that when we use the estimates to calculate the welfare losses, the figures turn out to be very similar (see Table 13). In Table 13 note that, using $IMH_2$, welfare loss per female is higher whereas loss per male is lower (compared to using $IMH_1$). The reason is that the coefficient of the female dummy is negative and significant (with a relatively high magnitude) in $IMH_2$, but insignificant in $IMH_1$.

8.2. Choice of the Utility Function

Since the analysis has been done using a Cobb-Douglas utility function, a natural question that emerges is how sensitive the results are to an alternative specification of the utility function. We redo our exercise with Constant Elasticity of Substitution (CES) utility function for the general model and get very similar results. The loss (using $IMH_1$) per month for a HIV male is Rs. 68,163 and for a HIV female is Rs. 65,729. Recall that the corresponding figures with the Cobb-Douglas utility function are Rs. 67,601 and Rs. 65,120 respectively. Thus our earlier results are robust.

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31 The details of the CES estimation are available from the authors on request.
The reason for the robustness lies in the fact that in almost all specifications in this family of CES utility functions, when calculating the money equivalent, the main loss comes from \( \frac{1+Z}{\delta_1} \). The money equivalent expression for CES function is given by

\[
\tau^j = \left[ \alpha \cdot \left( \frac{N^i}{\alpha} \right)^{\rho} + \beta \cdot \left( \frac{1/\delta_1}{\beta} \right)^{\rho} + \gamma \cdot \left( \frac{n_s^i}{\gamma} \right)^{\rho} \right]^{\frac{1-\rho}{\rho}} \left[ Y^i + \frac{1+Z^i}{\delta_1} + n_s^i \right] - \left[ Y^j + \frac{1+Z^j}{\delta_1} + n_s^j \right].
\]

Note that in this expression, the first part of the first term is close to one as neither the average family sizes nor the average numbers of school-going children are that different between the HIV and NON HIV families. This implies that, once again, the differences in \( Y \) and \( \frac{1+Z}{\delta_1} \) determine the loss. As before differences in \( \frac{1+Z}{\delta_1} \) is the dominant component of the loss and hence the results are similar.

9. Discussion of Results in Relation to the Literature

In this section we elaborate on our approach and results in reference to the relevant literature. Most of the studies have evaluated the cost of the HIV/AIDS epidemic in terms of the indirect and aggregative measures such as GDP per capita. These studies projecting the impact of HIV/AIDS on growth rate of per capita GDP use some version of the neoclassical growth model and typically estimate declines of 0.5% to 1.5% even for the worst-affected countries with more than 20% HIV prevalence rates. The key reason for these low estimates is that the increased labour productivity resulting from HIV/AIDS-induced increase in mortality reduces the population pressure on existing resources and goes a long way in offsetting all the negative effects of the disease. Young (2005) stretched the above logic as far as to project even higher living standards of the surviving future generations of South

Africa as “The Gift of the Dying” from the current generation with HIV/AIDS. To the above logic he added the decline of fertility associated with the HIV epidemic and, using South African data, estimated that the positive effects of lower population growth on real wages would be strong enough to more than offset even the most pessimistic forecasts of human capital losses due to HIV/AIDS. A similar logic is relevant for a labour surplus country like India and we do not expect to find much of an impact by taking the indirect approach working through the reduction in GDP growth rate of a booming economy with a low HIV/AIDS prevalence rate.

A growing body of relatively recent literature (see, for example, Ferreira and Pessoa, 2003; Bell, Devarajan and Gersbach, 2004, 2006; Corrigan, Gloom and Mendez, 2004, 2005; McDonald and Roberts, 2006) emphasizes the transmission of human capital across generations and concludes that by disrupting the mechanism that drives the process of the transmission of knowledge and abilities from one generation to the next, the AIDS epidemic will result in a substantial slowdown of economic growth. Part of the analysis relies on the dynamic implication of the mechanism that AIDS lowers investment in human capital of children since “… the expected pay-off (from this investment) depends on the level of premature mortality among the children when they attain adulthood” (Bell, Devarajan and Gersbach, 2006, page 59; our italics). This mechanism may be applicable for countries like South Africa and Kenya where the HIV/AIDS prevalence rate has reached 20% and 25% respectively, but is not quite relevant for India with a prevalence rate of just 0.9% where there are many other compelling reasons for not sending the children to schools.

Next, consider the literature that has used household data to find a considerable impact of HIV/AIDS through income, consumption and children’s education. Booysen and Bachmann (2002) find that the fall in per capita income in HIV households in South Africa is 40 to 50% while the fall in per capita food expenditure is 20 to 30%. In Indonesia, Gertler et al. (2003) find that death of a prime age male is associated with a 27% reduction in mean per capita household consumption. Many studies have reported negative impact of HIV/AIDS on children’s schooling. Deininger et al. (2003) show that foster children were at a distinct disadvantage in both primary and secondary school attendance before introduction of universal primary education. Gertler et al. (2003) find that orphans are less likely to start school and more likely to drop out. Yamano and Jayne (2005) and Evans and Miguel (2005) find the negative impact of adult mortality on school attendance of children to be more severe in poor households.
We are aware of only the following two works that are similar to ours in the use of some version of the principle of willingness to pay to calculate the economic cost of the disease. Crafts and Haacker (2004) use estimates and projections of the impact of HIV/AIDS on mortality rates and life expectancy, and drawing on existing studies on the value of statistical life (VSL), estimate the welfare loss of HIV/AIDS as the loss in income per capita that would have the same effect on lifetime utility as the increase in mortality. But the measure of welfare loss is entirely based on changes in mortality, whereas our measure allows for the impact of the disease on consumption, children’s schooling, physical and mental health. Further, the VSL estimates used may not be appropriate for the countries of interest as they are borrowed from studies on the VSL dealing with other countries typically with higher income and lower mortality. Our welfare loss estimates do not suffer from this problem as they are based on primary household data where we have allowed the data itself to determine the relative weights of different components in family preferences.

The other work by Bell (2005) sets up a nice conceptual framework using the principle of willingness to pay, captured in terms of compensating variation (CV) and equivalent variation (EV), to evaluate the direct costs of sickness and premature adult mortality. Unfortunately, he cannot estimate these costs as he does not have the empirical estimates of the required parameters. Instead he estimates the EV for Kenya using a model where there is no sickness but children’s human capital appears in the household’s preferences. He estimates that the EV is about six to nine times the loss in GDP per young adult.

Previously, mental health effects of HIV/AIDS have not been analysed. The integration of mental health in welfare evaluation becomes possible as medical expenditure, a choice variable in the family optimization problem, turns out to be a significant determinant of mental health. In the literature not related to HIV/AIDS, Blanchflower and Oswald (2004) is the only work we are aware of that has used the coefficients of subjective well-being equation to quantify welfare losses from incidence of divorce or job loss. But this quantification is not fully satisfactory as they have just compared the relative sizes of the coefficients of income and divorce in a regression equation like the one reported in Table 10, and calculated how income has to change to ‘compensate’ for divorce to maintain the same level of well-being and ignored the trade-off in the preferences or the budget constraint, which our model is able to take into account.
This paper develops simple measures of individual and family mental health indices based on axiomatic foundations and integrates mental health into the neoclassical model that allows for proper substitution possibilities in the family preferences and quantifies its significance in family utility along with its other arguments. It is an example of measuring and modelling what has traditionally been treated as part of unobserved heterogeneity in empirical models.

Using primary household data we estimate household utility function parameters that measure the relative importance of consumption, schooling of children and mental and physical health effects of HIV/AIDS in India. Since mental health is not directly observable, we first compute an ordinal measure based on a series of questions following Case and Deaton (2006). Then we use an ordered probit model to obtain a continuous measure based on medical expenditure, current health, wealth, HIV status, joint family status, age and sex. This measure is then used to estimate the parameters of the family utility function. The welfare loss due to HIV is then obtained using the principle of willingness to pay to come up to the utility level of non-HIV married families, used as the benchmark.

We find that mental health effects are far more important than the effect of consumption or children’s schooling in determining utility. The total annual loss for the country is approximately 7% of GDP (2004) and exceeds the annual health expenditure of the country in 2004. This huge magnitude is not surprising as it includes private valuation of one’s own life as well as the loss from stigma. The additional loss due to loss of labour income and increased medical expenditure measured by the external transfers accounts for 2.6% of the country’s health expenditure and 0.12% of GDP.

Besides the use of our mental health measure in other contexts, we hope our results will encourage future research to pay attention to factors that are typically treated as unobserved heterogeneity and attempt to obtain measures for them (even if crude). This may go a long way in improving our understanding of the issues of interest.
References


### Table 1: Family Types

<table>
<thead>
<tr>
<th>Family Types</th>
<th>HIV</th>
<th>NON HIV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Currently Married</td>
<td>0.61</td>
<td>0.71</td>
</tr>
<tr>
<td>Never married</td>
<td>0.14</td>
<td>0.22</td>
</tr>
<tr>
<td>Ever Married</td>
<td>0.25</td>
<td>0.07</td>
</tr>
</tbody>
</table>

### Table 2: Occupation Structure before Detection

<table>
<thead>
<tr>
<th>Occupation</th>
<th>Proportion of Males</th>
<th>Proportion of Females</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural Labourer</td>
<td>0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>Unskilled Worker</td>
<td>0.06</td>
<td>0.06</td>
</tr>
<tr>
<td>Truck Driver</td>
<td>0.06</td>
<td>0.00</td>
</tr>
<tr>
<td>Auto/Taxi/Car/Bus Driver</td>
<td>0.10</td>
<td>0.00</td>
</tr>
<tr>
<td>Industry and factory worker</td>
<td>0.26</td>
<td>0.03</td>
</tr>
<tr>
<td>Hotel Staff</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Business Owner</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Petty Shop Owner</td>
<td>0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>Housewife</td>
<td>0.00</td>
<td>0.60</td>
</tr>
<tr>
<td>Student</td>
<td>0.04</td>
<td>0.02</td>
</tr>
<tr>
<td>Other Services</td>
<td>0.05</td>
<td>0.02</td>
</tr>
<tr>
<td>Unemployed</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Other Occupations</td>
<td>0.24</td>
<td>0.10</td>
</tr>
</tbody>
</table>
### Table 3: Physical Health Index

<table>
<thead>
<tr>
<th></th>
<th>Health index</th>
</tr>
</thead>
<tbody>
<tr>
<td>HIV</td>
<td></td>
</tr>
<tr>
<td>Male:</td>
<td>7.8 (1.8)</td>
</tr>
<tr>
<td>Female:</td>
<td>8.6 (1.9)</td>
</tr>
<tr>
<td>Average Family</td>
<td>8.5 (1.5)</td>
</tr>
<tr>
<td>NON HIV</td>
<td></td>
</tr>
<tr>
<td>Male:</td>
<td>10.3 (1.1)</td>
</tr>
<tr>
<td>Female:</td>
<td>10.5 (0.9)</td>
</tr>
<tr>
<td>Average Family</td>
<td>10.3 (0.8)</td>
</tr>
</tbody>
</table>

(Standard errors are in the parentheses.)

### Table 4: Mental Health: Relative Frequency (in %)

<table>
<thead>
<tr>
<th></th>
<th>HIV families</th>
<th>NON HIV families</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IMH₁</td>
<td>IMH₂</td>
</tr>
<tr>
<td>Most of the time (1)</td>
<td>82.43</td>
<td>57.77</td>
</tr>
<tr>
<td>Sometimes (2)</td>
<td>14.05</td>
<td>28.34</td>
</tr>
<tr>
<td>Hardly Ever (3)</td>
<td>3.24</td>
<td>7.36</td>
</tr>
<tr>
<td>Never (4)</td>
<td>0.27</td>
<td>6.54</td>
</tr>
</tbody>
</table>

### Table 5: Employment Transitions of HIV Patients

<table>
<thead>
<tr>
<th>BHD State</th>
<th>Current State</th>
<th>Probability of moving into</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Employed</td>
</tr>
<tr>
<td>Employed</td>
<td></td>
<td>Employed</td>
</tr>
<tr>
<td>Males:</td>
<td>0.80</td>
<td>0.20</td>
</tr>
<tr>
<td>Females:</td>
<td>0.90</td>
<td>0.10</td>
</tr>
</tbody>
</table>
### Table 6: Physical Health Index of those Supplying Outside Labour

<table>
<thead>
<tr>
<th></th>
<th>NON HIV</th>
<th>HIV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male Labour Supply $l_m &gt; 0$</td>
<td>10.34 (0.97)</td>
<td>8.09 (1.72)</td>
</tr>
<tr>
<td>Male Labour Supply $l_m = 0$</td>
<td>10.08 (1.66)</td>
<td>7.02 (2.03)</td>
</tr>
<tr>
<td>Female Labour Supply $l_f &gt; 0$</td>
<td>10.45 (0.99)</td>
<td>8.53 (1.75)</td>
</tr>
<tr>
<td>Female Labour Supply $l_f = 0$</td>
<td>10.57 (0.82)</td>
<td>8.72 (2.00)</td>
</tr>
</tbody>
</table>

(Standard errors are in the parentheses.)

### Table 7: Effect on Children’s Education

<table>
<thead>
<tr>
<th></th>
<th>Proportion Attendance (Ps) (Age: 6-18)</th>
<th>Quality Adjusted Attendance</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>HIV Families</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Widow</td>
<td>0.74 (0.40)</td>
<td>71 (119)</td>
</tr>
<tr>
<td>Widower</td>
<td>0.75 (0.43)</td>
<td>106 (156)</td>
</tr>
<tr>
<td>Currently Married</td>
<td>0.93 (0.23)</td>
<td>152 (234)</td>
</tr>
<tr>
<td><strong>NON HIV families</strong></td>
<td>0.89 (0.27)</td>
<td>132 (154)</td>
</tr>
</tbody>
</table>

(Standard errors are in the parentheses.)
Table 8: Income and Expenditure (Rs. per Month)

<table>
<thead>
<tr>
<th>Family Type</th>
<th>HIV</th>
<th>NON HIV</th>
<th>t values (H0: Means equal)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td><em>(One tail test : $H_A \mid \text{Mean}_1 - \text{Mean}_2 &gt; 0)</em></td>
</tr>
<tr>
<td>Currently Married</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>930</td>
<td>1109</td>
<td>1.87: Rejected at 5%*</td>
</tr>
<tr>
<td></td>
<td>(1116)</td>
<td>(1121)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Consumption Expenditure</td>
<td>760</td>
<td>690</td>
<td>1.10: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(721)</td>
<td>(764)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Medical Expenditure</td>
<td>190</td>
<td>69</td>
<td>5.80: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(276)</td>
<td>(186)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Schooling Expenditure</td>
<td>40</td>
<td>37</td>
<td>0.51: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(75)</td>
<td>(56)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Dissaving and External Funding</td>
<td>60</td>
<td>-312</td>
<td>4.5: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(913)</td>
<td>(1039)</td>
<td></td>
</tr>
<tr>
<td>Never Married</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>2054</td>
<td>2171</td>
<td>0.23: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(3156)</td>
<td>(2510)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Consumption Expenditure</td>
<td>2664</td>
<td>2123</td>
<td>1.77: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(1873)</td>
<td>(1556)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Medical Expenditure</td>
<td>1675</td>
<td>237</td>
<td>1.44: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(7069)</td>
<td>(578)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Dissaving and External Funding</td>
<td>2285</td>
<td>188</td>
<td>1.89: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(7639)</td>
<td>(2594)</td>
<td></td>
</tr>
<tr>
<td>Ever Married (Widows)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>541</td>
<td>178</td>
<td>2.13: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(1314)</td>
<td>(224)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Consumption Expenditure</td>
<td>753</td>
<td>419</td>
<td>2.7: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(831)</td>
<td>(285)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Medical Expenditure</td>
<td>159</td>
<td>29</td>
<td>3.72: Rejected at 5% *</td>
</tr>
<tr>
<td></td>
<td>(272)</td>
<td>(41)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Schooling Expenditure</td>
<td>25</td>
<td>18</td>
<td>0.65: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(55)</td>
<td>(34)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Dissaving and External Funding</td>
<td>396</td>
<td>288</td>
<td>0.61: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(1134)</td>
<td>(439)</td>
<td></td>
</tr>
<tr>
<td>Ever Married (Widowers)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Capita Income</td>
<td>1375</td>
<td>1969</td>
<td>0.68: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(2264)</td>
<td>(2033)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Consumption Expenditure</td>
<td>706</td>
<td>901</td>
<td>0.59: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(663)</td>
<td>(798)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Medical Expenditure</td>
<td>349</td>
<td>254</td>
<td>0.43: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(550)</td>
<td>(472)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Schooling Expenditure</td>
<td>56</td>
<td>6</td>
<td>2.51: Rejected at 5%</td>
</tr>
<tr>
<td></td>
<td>(78)</td>
<td>(11)</td>
<td></td>
</tr>
<tr>
<td>Per Capita Dissaving and External Funding</td>
<td>-264</td>
<td>-808</td>
<td>0.96: Accepted at 5%</td>
</tr>
<tr>
<td></td>
<td>(1207)</td>
<td>(1351)</td>
<td></td>
</tr>
</tbody>
</table>

*(One tail test : $H_A \mid \text{Mean}_1 - \text{Mean}_2 > 0$)*
Table 9: Weights

<table>
<thead>
<tr>
<th>POPULATION</th>
<th>Number/ Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Total Population 15-49</td>
<td>521397817</td>
</tr>
<tr>
<td>B. Number of HIV positive adult males</td>
<td>1550000</td>
</tr>
<tr>
<td>C. Number of HIV positive adults females</td>
<td>950000</td>
</tr>
<tr>
<td>D. Total Number of HIV positive adults</td>
<td>2500000</td>
</tr>
<tr>
<td>E. Prob of meeting a adult HIV male (B/A)</td>
<td>0.002972778</td>
</tr>
<tr>
<td>F. Prob of meeting an adult HIV females (C/A)</td>
<td>0.001822025</td>
</tr>
<tr>
<td>G. Prob of meeting an adult NONHIV male</td>
<td>0.514800642</td>
</tr>
<tr>
<td>H. Prob of meeting an adult NONHIV female</td>
<td>0.480404555</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>SAMPLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Proportion of respondent HIV positive adult males</td>
</tr>
<tr>
<td>J. Proportion of respondent HIV positive adults females</td>
</tr>
<tr>
<td>K. Proportion of respondent NON HIV adult males</td>
</tr>
<tr>
<td>L. Proportion of respondent NON HIV adults females</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>WEIGHTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>M. Weight on HIV positive adult male (E/I)</td>
</tr>
<tr>
<td>N. Weight on HIV positive adult female (F/J)</td>
</tr>
<tr>
<td>O. Weight on NON HIV adult male (G/K)</td>
</tr>
<tr>
<td>P. Weight on NON HIV adult female (H/L)</td>
</tr>
</tbody>
</table>
Table 10: Mental Health: Ordered Probit Estimates

<table>
<thead>
<tr>
<th></th>
<th>IMH₁</th>
<th>IMH₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>md</td>
<td>0.000018**</td>
<td>0.000016*</td>
</tr>
<tr>
<td>H</td>
<td>0.248***</td>
<td>0.172***</td>
</tr>
<tr>
<td>ts</td>
<td></td>
<td>0.098**</td>
</tr>
<tr>
<td>W</td>
<td>0.00000146***</td>
<td></td>
</tr>
<tr>
<td>D_{HIV}</td>
<td>-1.20***</td>
<td>-1.73***</td>
</tr>
<tr>
<td>D_{FEM}</td>
<td></td>
<td>-0.71***</td>
</tr>
<tr>
<td>D_{EXT}</td>
<td>0.68***</td>
<td></td>
</tr>
<tr>
<td>Av_age</td>
<td></td>
<td>-0.87**</td>
</tr>
<tr>
<td>Av_age²</td>
<td>0.0002*</td>
<td>0.001**</td>
</tr>
<tr>
<td>D_{NORTH}</td>
<td>-0.26*</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>829</th>
<th>833 #</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Observations</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Pseudo Likelihood</td>
<td>-432.92</td>
<td>-799.60</td>
</tr>
<tr>
<td>χ²</td>
<td>181.90***</td>
<td>369.79***</td>
</tr>
<tr>
<td>Pseudo R²</td>
<td>0.10</td>
<td>0.09</td>
</tr>
</tbody>
</table>

(* significant at 1%, ** significant at 5% and * significant at 10%)
#: No. of Observations differ due to missing data.

Table 11: Estimates from Consumption, Schooling and the Transformed Medical Expenditure Equation

<table>
<thead>
<tr>
<th></th>
<th>With School Age-Children (n_s &gt; 0)</th>
<th>With School Age-Children (n_s &gt; 0)</th>
<th>Without School Age-Children (n_s = 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  ^{\hat{\phi}}₁</td>
<td>0.014***</td>
<td>0.0172***</td>
<td></td>
</tr>
<tr>
<td>2  ^{\hat{\phi}}₂</td>
<td>0.002***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>326</th>
<th>326</th>
<th>348</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Observations</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.68</td>
<td>0.49</td>
<td>0.67</td>
</tr>
</tbody>
</table>

(* significant at 1%)
Table 12: Partial Effects on CV ($\tau^j$)

<table>
<thead>
<tr>
<th>Partial Effects ($IMH_1$)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$H^i - H^j$</td>
<td>13,652</td>
</tr>
<tr>
<td>$W^i - W^j$</td>
<td>0.08</td>
</tr>
<tr>
<td>$D_{HIV}$</td>
<td>-66,039</td>
</tr>
<tr>
<td>$D_{EXT}$</td>
<td>37,600</td>
</tr>
<tr>
<td>$Av_age^2_i - Av_age^2_j$</td>
<td>12.26</td>
</tr>
</tbody>
</table>

Table 13: Welfare Loss: All-India

<table>
<thead>
<tr>
<th>Loss using $IMH_1$</th>
<th>Loss using $IMH_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per HIV+ Male</td>
<td>Per Month (Rs.)</td>
</tr>
<tr>
<td>67,601</td>
<td>104.78</td>
</tr>
<tr>
<td>76,986</td>
<td>119.32</td>
</tr>
</tbody>
</table>

Table 14: OLS Regression: Welfare Losses and Losses from Transfers on Family Types

<table>
<thead>
<tr>
<th>Welfare Loss Per Month (Rs.)</th>
<th>Losses from Transfers Per Month (Rs.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>Coefficients</td>
</tr>
<tr>
<td>Constant</td>
<td>86,217***</td>
</tr>
<tr>
<td>Only Female HIV Married Families</td>
<td>-18,335**</td>
</tr>
<tr>
<td>Both HIV Married Families</td>
<td>6067*</td>
</tr>
<tr>
<td>Widow HIV Families</td>
<td>7,143*</td>
</tr>
<tr>
<td>Widower HIV Families</td>
<td>-4,756</td>
</tr>
<tr>
<td>Never Married Male Families</td>
<td>701</td>
</tr>
<tr>
<td>Never Married Female Families</td>
<td>-176</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>No. of Observations</th>
<th>369</th>
<th>369</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.03</td>
<td>0.02</td>
</tr>
</tbody>
</table>

(*** significant at 1%, ** significant at 5% and * significant at 10%)
### Table 15: Disaggregates of Monetary Equivalent of Welfare Losses

<table>
<thead>
<tr>
<th></th>
<th>$Y$</th>
<th>$N$</th>
<th>$n_s$</th>
<th>$\frac{1+Z}{\delta_i}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>With School-Age Children</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NON HIV Married Families</td>
<td>2,410</td>
<td>4.41</td>
<td>2.13</td>
<td>231,133</td>
</tr>
<tr>
<td>Only Male HIV Married Families</td>
<td>2,593</td>
<td>4.05</td>
<td>2.01</td>
<td>146,485</td>
</tr>
<tr>
<td>Only Female HIV Married Families</td>
<td>2,587</td>
<td>3.83</td>
<td>1.83</td>
<td>162,066</td>
</tr>
<tr>
<td>Both HIV Married Families</td>
<td>3,176</td>
<td>4.00</td>
<td>1.80</td>
<td>141,425</td>
</tr>
<tr>
<td>Widow HIV Families</td>
<td>2,149</td>
<td>3.21</td>
<td>1.85</td>
<td>136,664</td>
</tr>
<tr>
<td><strong>Without School-Age Children</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NON HIV Married Families</td>
<td>2,639</td>
<td>2.60</td>
<td>0</td>
<td>239,028</td>
</tr>
<tr>
<td>Only Male HIV Married Families</td>
<td>2,879</td>
<td>2.67</td>
<td>0</td>
<td>151,760</td>
</tr>
<tr>
<td>Only Female HIV Married Families</td>
<td>3,825</td>
<td>2</td>
<td>0</td>
<td>170,122</td>
</tr>
<tr>
<td>Both HIV Married Families</td>
<td>3,442</td>
<td>2.8</td>
<td>0</td>
<td>143,869</td>
</tr>
<tr>
<td>Widow HIV Families</td>
<td>1,676</td>
<td>1.45</td>
<td>0</td>
<td>143,988</td>
</tr>
</tbody>
</table>

### Table 16: Contribution to Welfare Losses

<table>
<thead>
<tr>
<th></th>
<th>$H$</th>
<th>$W$</th>
<th>$D_{nv}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>With School-Age Children</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only Male HIV Married Families</td>
<td>16,213</td>
<td>424.39</td>
<td>66,039</td>
</tr>
<tr>
<td>Only Female HIV Married Families</td>
<td>10,570</td>
<td>967.69</td>
<td>66,039</td>
</tr>
<tr>
<td>Both HIV Married Families</td>
<td>24,759</td>
<td>-561.16</td>
<td>66,039</td>
</tr>
<tr>
<td>Widow HIV Families</td>
<td>36,482</td>
<td>442.37</td>
<td>66,039</td>
</tr>
<tr>
<td><strong>Without School-Age Children</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Only Male HIV Married Families</td>
<td>21,353</td>
<td>8.43</td>
<td>66,039</td>
</tr>
<tr>
<td>Only Female HIV Married Families</td>
<td>5,890</td>
<td>1311.79</td>
<td>66,039</td>
</tr>
<tr>
<td>Both HIV Married Families</td>
<td>24967</td>
<td>-162.62</td>
<td>66,039</td>
</tr>
<tr>
<td>Widow HIV Families</td>
<td>28,451</td>
<td>1045.97</td>
<td>66,039</td>
</tr>
</tbody>
</table>
### Table A.1: Summary Statistics (money values in Rupees and time in years)

<table>
<thead>
<tr>
<th>Description</th>
<th>Mean</th>
<th>Std Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per Capita Monthly Consumption Expenditure ($c$)</td>
<td>1,019</td>
<td>1,189</td>
</tr>
<tr>
<td>Quality Adjusted School Attendance ($P_S \cdot SC$)</td>
<td>70</td>
<td>170</td>
</tr>
<tr>
<td>Medical Expenditure ($md$)</td>
<td>591</td>
<td>2,748</td>
</tr>
<tr>
<td>Family Size ($N$)</td>
<td>2.9</td>
<td>1.38</td>
</tr>
<tr>
<td>Average Physical Health of Family ($H$)</td>
<td>8.5</td>
<td>1.44</td>
</tr>
<tr>
<td>Time Span since HIV Detection ($ts$)</td>
<td>2.07</td>
<td>1.71</td>
</tr>
<tr>
<td>Square of Time Span since HIV Detection ($ts^2$)</td>
<td>7.23</td>
<td>9.5</td>
</tr>
<tr>
<td>Wealth ($W$)</td>
<td>18,634</td>
<td>50,168</td>
</tr>
<tr>
<td>Number of School Going Age Children ($n_s$)</td>
<td>1.04</td>
<td>1.24</td>
</tr>
<tr>
<td>Family Resides in North India ($D_{NORTH}$)</td>
<td>0.52</td>
<td>0.49</td>
</tr>
<tr>
<td>Family has Female Adult Member ($D_{FEM}$)</td>
<td>0.80</td>
<td>0.39</td>
</tr>
<tr>
<td>Patient Lives in an Extended Family ($D_{EXT}$)</td>
<td>0.63</td>
<td>0.48</td>
</tr>
<tr>
<td>Family has at least one Unemployed Adult ($D_{UNEMP}$)</td>
<td>0.12</td>
<td>0.32</td>
</tr>
<tr>
<td>Average Age of Adult Members ($Av_{age}$)</td>
<td>32.4</td>
<td>8.7</td>
</tr>
<tr>
<td>Square of Average Age of Adult Members ($Av_{age}^2$)</td>
<td>1,125</td>
<td>659</td>
</tr>
</tbody>
</table>
### Table A.2: Mental Health: Ordered Probit Estimates

<table>
<thead>
<tr>
<th></th>
<th>IMH₁</th>
<th>IMH₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>D_{NORTH}</td>
<td>-0.056</td>
<td>-0.24</td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>md</td>
<td>0.00000191**</td>
<td>0.0000181*</td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>H</td>
<td>0.276***</td>
<td>0.176***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>ts</td>
<td>-0.21</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.88)</td>
</tr>
<tr>
<td>ts²</td>
<td>0.03</td>
<td>0.21</td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>W</td>
<td>0.0000012**</td>
<td>0.00000049</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.67)</td>
</tr>
<tr>
<td>D_{HIV}</td>
<td>-0.90***</td>
<td>-1.61***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>D_{FEM}</td>
<td>-0.32</td>
<td>-0.70***</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>D_{EXT}</td>
<td>0.55***</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.854)</td>
</tr>
<tr>
<td>D_{UNEMP}</td>
<td>-0.331</td>
<td>-0.16</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.39)</td>
</tr>
<tr>
<td>Av_Age</td>
<td>-0.05</td>
<td>-0.087*</td>
</tr>
<tr>
<td></td>
<td>(0.27)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Av_Age²</td>
<td>0.0009</td>
<td>0.0013**</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

|                | No. of Observations  | 829                   | 820*  |
| Log Pseudo Likelihood | -424.34              | -784.87               |
| χ²             | 187.99***            | 369.79***             |
| Pseudo R²      | 0.12                 | 0.09                  |

(* * * significant at 1%, ** significant at 5% and * significant at 10%)

#: No. of Observations differ due to missing data.

### Table A.3: Joint Test of Significance

<table>
<thead>
<tr>
<th></th>
<th>IMH₁</th>
<th>IMH₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>H₀: D_{NORTH} = ts = ts² = D_{FEM} = D_{UNEMP} = Av_Age = 0</td>
<td></td>
<td>H₀: ts² = W = D_{UNEMP} = D_{EXT} = 0</td>
</tr>
<tr>
<td>Verdict: Cannot reject H₀</td>
<td></td>
<td>Verdict: Cannot reject H₀</td>
</tr>
<tr>
<td>χ² (7) = 6.97</td>
<td></td>
<td>χ² (6) = 2.26</td>
</tr>
<tr>
<td>Prob &gt; χ² = 0.32</td>
<td></td>
<td>Prob &gt; χ² = 0.69</td>
</tr>
</tbody>
</table>