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The Effect of Parental Death on Children's Wellbeing

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By

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I. Abstract

A parent's death can have a lasting impact on a child's outcomes. This paper analyzes the effect of parental death on a child's workforce participation, education, marital status and health, and a household's consumption. I compare outcomes for if a mother passes away versus if a father passes away, and for girls versus boys. I run traditional Ordinary Least Squares (OLS) regressions, but recognize that endogeneity and identification problems may cause OLS estimates to be biased. I therefore use Propensity Score Matching (PSM) in an attempt to mitigate misattribution, and estimate the average treatment effect (ATE) and the average treatment effect on the treated (ATET) for each dependent variable. I compare these PSM results to those from OLS regressions. I find that on average, parental death leads to worse outcomes on most indicators of a child's wellbeing. A parent's death has a larger and more negative effective on a daughter's outcomes than a son's. The data presents worse effects on a child from a mother passing away on some indicators, and worse outcomes from a father passing away on others.

II. Introduction

Parental death is a life-changing shock. In addition to the psychological and emotional toll on the remaining household members, a parent's death also has measurable, lasting impact on one's socioeconomic wellbeing indicators. This paper explores the short term (5-9 years after death) effects on a child of losing a parent in India. I measure the impact on a child's likelihood to be working, school enrollment, grades of education completed, likelihood to get married, and the number of days a child was sick in the 30-day period before the data gathering interview was conducted. I also look at the effect of parental death on a household's monthly consumption per capita.

While I do regress my chosen outcomes using the OLS model, an OLS regression can result in biased estimates of independent variables because of endogeneity, which the model can suffer from when an explanatory variable, such as parental death, is correlated with the error term, which might include uncontrolled confounders that may have an effect on the dependent variable and also be correlated with both independent and dependent variables in a model. For example, one can imagine a scenario in which a parent suffered from mental illness, which created an unsafe environment for a child to grow up in and thus reduced the amount of education attained by the child. Parental mental illness may have increased the likelihood of the parent to die to die, but it may also have caused the child to receive less education than a child with a mentally healthy parent. Using OLS, one attempts to balance observations on observed independent variables, but cannot be sure that observations are balanced on other unobserved, relevant factors. Households which are likely to lose a parent may be different from households which do not lose a parent, so I use propensity score matching to compare households which lost a parent to ones which did not, by matching treatment and control households on observable variables. I then compare these outcomes to those per OLS regressions.

I define children as those 18 or younger in round 1, and treatment as losing a parent between rounds 1 and 2. I try to carefully build treatment and control groups that are balanced on observables by construction, and hopefully on unobservables in the end as well. At the time of the first round of surveys (Table 1: Round 1 Summary Statistics, Treatment v Control), those in the eventually treated group were more likely to lose a parent. The treated children were on average 2 years older and lived in households with 500 rupees/capita more debt, compared to those in the control group. The parents of the treated were also older. Mothers on average were 5 years older and fathers on average were 6 years older for treated children, compared to parents of the control.

Parents of the treated were more likely to be using tobacco/alcohol, and were diagnosed with serious illnesses such as cancer, diabetes, heart disease and tuberculosis more often than the parents of the control children, with fathers of the treated group being diagnosed with a serious illness three times as often as those of the control. Because the treated households are significantly different from the control households, it would be incorrect to assume that treatment was randomly assigned to the sample, and the data would be biased if I did. Counterintuitively, parents of the treated, on average, had one more year of education than parents of the control, though as one might expect, the mothers had less education than the fathers – about one year less for both the treatment and control mothers.

A second treatment level I investigate is the effect of a mother's death versus a father's death. I compare the summary descriptive statistics (Table 2: Round 1 Summary Statistics, Treated – Mother Died v Father Died) of the children who lost a mother between rounds 1 and 2 to those who lost a father. Those who lost a mother were, on average, one year younger, lived in slightly larger households, had mothers who were diagnosed with serious illnesses three times more often, had a mother who had completed about 0.80 years less schooling, and had 50 rupees of a lower monthly household consumption per capita. Those who lost a father were on average one year older, had fathers who had been diagnosed with serious illnesses almost 4 times more often, were in households with 1,460 rupees/capita of greater debt, and had fathers about 3.5 years older. Counterintuitively, those who lost a mother had mothers who were 1.74 years younger on average.

This paper is organized as follows: Section III is a review of the existing literature about the effect of parental death on children's socioeconomic well being indicators. Section IV describes the IHDS dataset used. Section V describes the regression models used, including a background of propensity score matching. Section VI describes the results, Section VII explains the shortcomings of this paper and avenues for further research, and Section VIII concludes. Section IX presents summary statistics and regression tables.

III. Literature Review

Studies show how parental death can contribute to a child's future outcomes, and that it is not a trivial problem. I estimate the effect of parental death on a child's wellbeing outcomes, including workforce participation, enrollment in school, education level completed, marital status, health, the household's expenditure on the child's education, and the household's monthly income per capita. In this section I review the existing economics literature for commonly accepted theories and mechanisms by which parental death affects a child's future outcomes. I also look at evidence for a difference in the effect of the death of a mother versus the death of a father, and the difference in the effect of parental death on a girl-child versus the effect on a boy-child. The number of years which have passed between a parent's death and the measurement of an outcome also help determine the magnitude of the effect. Previous researchers have noted that the more time that has elapsed since parental death, the more adapted and recovered a household may be from the initial shock. The literature also points to a difference in the effect of parental death on younger children versus on adult/near-adult children.

Cosic and Deb (2010) examine the effects of adult mortality on education, health and food. They look at how the HIV/AIDS epidemic of 2003 in the South African province of KwaZulu-Natal claimed 47% of deaths overall, and 71% of deaths in the 15-49 age strata. The authors use the KwaZulu-Natal Income Dynamics Study (KIDS) panel dataset, which follows 1,377 households originally surveyed in 1993 under the Project for Statistics on Living Standards and Development, in 1998 and 2004. Cosic and Deb find that a death in a household decreases that household's consumption of food and education, but find no impact on healthcare expenditure. Furthermore, the authors find no difference between the effect of mother death and father death, which they attribute to a lack of statistical power, rather than claiming no significant difference in effect of mother versus father death.

Cosic and Deb use a difference-in-difference (DID) design to take into account possible systematic differences between origin households and their split-off households. They are able to use a DID design because they have three rounds of data, and thus are able to better de-trend and account for the different rates at which outcomes of treated and control households change than I am. My dataset has only two rounds, which may result in biased conclusions if I use a DID design, because even if I subtract out different starting points, treated households may be on a different trend line than control households. However, I am able to further Cosic and Deb's work because unlike the KIDS dataset they use, the IHDS dataset allows me to estimate the difference between the effect of a mother's death versus a father's death.

One repeated finding is that when children are not enrolled in school, they are not necessarily out of work (idle), and when a child is working, s/he has not necessarily dropped out of school. Bhatty (1998) notes that a child might concurrently be attending school and working, while another might be neither attending school, nor working. Maitra and Ray (2002), Rosati and Tzannatos (2006), and Das (2016) account for the four different combinations of enrollment and work, ranked highest to lowest based on the child's welfare: enrolled and do not work, enrolled and work, neither enrolled nor work, and not enrolled and work. Seck (2010) uses a multinomial logit model to estimate children's school enrollment and workforce participation activities before and after they lose a parent. Das (2016) found that school enrollment of older (ages 12 to 18) one-parent children was significantly lower than for older dual-parent children. Those left with only a father were the least likely to be enrolled.

When a parent passes away, a household may reallocate its dispensable income. Das (2016) discusses the effect of single parenthood on education-related inputs among school-aged children in India. He found one-parenthood was associated with significantly higher education expenditures among younger (ages 6-11) children, but no significant effect existed for older children. Separated or divorced mothers on average spent less on education than the other parent groups. Das also found that education-related expenditures were lowest for children with only a father.

Whereas Das (2016) only had round 1 of the IHDS dataset available, I further his research by using round 2 data to create a panel dataset. His was cross-sectional data and thus he was unable to attribute any causality to single-parenthood. Furthermore, the effects of a mortality shock to a household are more fleshed out over time, and the 5-9 years between the two rounds of surveys allow me to account for this. While I hope that I reduce potentially unobserved heterogeneity and selection biases by matching on as many relevant variables as I can identify using propensity score matching, I cannot be 100% sure that the observations in the control and treatment groups are balanced. I do not know whether unobserved variables such as parent's mental health or family's level of dysfunctionality are also correlated with the observed variables, as my dataset does not include such variables.

A household may need to rely on an additional set of earning hands after the loss of a breadwinner and/or caretaker of children. Das notes older (ages 12-18) children of widows are the most likely to be working. He found one-parenthood to be associated with a significantly higher probability of working and not being enrolled in school, among this group of older children.

Throughout the world, and especially so in developing countries, girls are well documented to be treated as second-tier citizens and discriminated against compared to boys. Cameron and Worswick (2001) and Rose (1999) show that because women's labor market opportunities are already limited in developing countries like India, daughters, compared to sons, bear a disproportionate burden from negative shocks to a household, such as the death of a parent.

IV. Data

I used the India Human Development Survey panel dataset put together by the University of Maryland and the National Council of Applied Economic Research (NCAER), a New Delhi based nonprofit economics think tank. The IHDS includes two rounds of nationally representative surveys across India, covering various topics including health, education and economics.

Round 1 data was collected between November 2004 and October 2005. It includes 215,754 individuals across 41,554 households, from 1,503 villages and 971 urban neighborhoods in 33 states and union territories of India. Round 2 data was collected between January 2011 and May 2013. It includes 204,569 individuals across 42,152 households, from 1,420 villages and 1,042 urban neighborhoods in all states and union territories of India with the exception of the Andaman and Nicobar and Lakshadweep islands.

The merged dataset is made of 150,988 individuals from 40,018 households. In urban blocks and rural areas of northeastern states where 5 or more IHDS households were lost to attrition, interviewers were asked to inform NCAER of this loss, and after a loss was verified by a physical visit, a replacement household was randomly selected from the same neighborhood the missing household was located in. This led to 2,134 new, replacement households being included in the IHDS-II sample.

Based on the date ranges of when interviews were conducted, second round interviews must be at least 5 years after a first round interview, and at most, 9 years could have elapsed between the two rounds. Of 52,958 children in round 2 who are coded as having been 18 or younger in round 1, I find and drop 4,606 (8.70%) who are coded as having been interviewed in round 2 outside of this time range – either too much or too little time is coded as having elapsed since the individual was first interviewed in round 1. 8.08% of the 4,606 individuals I drop are coded as having lost a parent between rounds 1 and 2, whereas only 5.27% of the children I keep in the analysis are coded as having lost a parent between the two rounds. If ages had been correctly coded, one might anticipate that the effect of parental death on a child's outcomes would be even larger and more negative. For the subset of individuals that I do analyze, I am left with 48,352 children who were 18 or younger in round 1. 20,813 (43.04%) of these children are girls. 637 (0.01%) children lost a mother, 1,861 lost a father (0.04%) and 48 lost both.

I create a morbidity indicator variable, using a morbidity scale which ranges from 0 to 15, for how many serious illnesses a parent suffers from and has been diagnosed with, i.e. cancer, diabetes, heart disease and tuberculosis. I also create a Sanitation Index, a range from 0 to 3, with one point each for if a person uses a toilet (versus defecating in "open fields"), if the person washes her/his hands after defecation, and if the person uses soap to wash hands after defecation.

V. Model, Regression Analyses

For the purposes of this paper, I first generate a variable *treatment* that is equal to 1 for those individuals 18 years of age or younger (whom I refer to as children) in round 1 of the IHDS survey, who lose a parent between rounds 1 and 2 of the survey. When randomization of a treatment such as parental death is not possible, propensity score matching serves as a substitute, by creating a subgroup of observations that can serve as a control group comparable to the treated observations, based on similarity on the observed independent variables. Per Rosenbaum and Rubin (1983), matching on a single "index" such as the propensity score can just as effectively calculate the treatment effect, as matching on all variables.

Using PSM, first assigns each individual a likelihood of being treated, which in this case means losing a parent between rounds 1 and 2. Then I compare those children who were treated with those who have a similar/the closest propensity score, but were part of the control group. PSM compares treated households to control households, by a household's probability of parental death. There may be something different about households which end up losing a parent when compared to households that do not lose a parent. For example, one might hypothesize that a treated household is likely poorer, has less educated parents, and has parents who work in more hazardous occupations such as manual labor or in manufacturing/industrial settings, compared to control households, which may be wealthier on average, and have parents who work desk or corporate jobs such as lawyers or accountants.

Dahejia and Wahba (2002) discuss propensity score matching methods, which in the late 1990s were a relatively new econometric tool available to control for sample bias. They define a propensity score as the probability of receiving treatment, conditional on covariates. To isolate the true, unbiased estimate of treatment on the treated, the outcome in the control group should be independent of whether an observation received treatment.

One matches an observation in the treatment group to an observation in the control group, based on whether the control observation's propensity score is reasonably close to that of the treated observation. There are three main methods to choose from: (i) matching with replacement, under which one matches a treated observation to a control one and then includes that matched control observation back in the pool to choose from, for the next treated observation to be matched, (ii) nearest neighbor, under which one matches a treated observation to a control observation based on which control observation has the closest propensity score to the treated observation, and (iii) caliper matching, under which one builds groups of control observations which fall within a range of propensity score radii, and then uses all of the control units within this range as comparables for a set of treated outcomes also within this same range of propensity score radii.

If one matches without replacement, each treated observation is matched to a unique control observation based on the nearest propensity score. While using more comparison units increases the precision of estimates, it also results in increased bias. If one compares each treatment observation to a unique control observation, one has come up with the smallest difference in propensity score between the treatment and comparison observations. However, if there are only a few observations in the control group, one may be forced to match with units with large differences in propensity scores.

Each individual has two potential outcomes – one if the individual is treated (parental death in this case), and the other if the individual is not. An individual's treatment effect is the difference between these two potential outcomes. However, because an individual cannot concurrently be treated and left untreated, one instead calculates the average treatment effect (ATE), which is the average effect of treatment across the entire population. This includes the effect of treatment on those who were treated, plus the estimated effect of treatment on those who were not treated, had they been treated. The average outcome among the treated is the counterfactual for the average among the control observations (Holland, 1986). The ATE is the difference between this mean of the outcomes of the treated and the mean of the outcomes of the control observations. I also calculate the average treatment effect on the treated (ATET), which is simply the effect of treatment only for those children who actually received treatment. To use propensity score matching, one must assume that the distribution of potential outcomes and of observed and unobserved characteristics, the covariates, are the same for both control and treatment households, and that the distributions of observed and unobserved characteristics are independent of each other.

I also add mother death and father death as additional treatments, to measure the differences in the effect of a mother's death versus a father's death. I compare the effect of each of these types of parental death with parent death of the other gender, as well as with the control, which in this case is the children who lost no parents plus the children who lost a parent of the opposite gender. Finally, I interact being a female child and treatment, to measure the effect of parental death on girls versus on boys.

I use the teffects psmatch command in STATA, which accepts a continuous, binary, count, fractional, or non-negative outcome. The more variables ("dimensions") on which one needs to match control and treatment observations, the more difficult it becomes to find comparable individuals, because one is looking for two people who are similar on more and more criteria. Using a PSM model, one can only hope that the observations in the control and treatment groups are balanced, but cannot be sure whether the unobserved variables are correlated with the observed variables. I use PSM because I am concerned that unobserved characteristics of a household may lead the estimates of the effect of the observed characteristics to be biased, and might over or under-attribute effects to death.

For example, a dysfunctional family, an unobserved variable, might increase the likelihood of a parent's death, an independent variable, but might also decrease the level of education a child attains. The independent variables should be exogenous, and the effect of the unobserved variable on the dependent variable should be attributed to dysfunctionality of family, not incorrectly to an independent variable such as parental death. When the unobserved effect is large and negative, so is the error term, as well as the incorrect attribution of the effect of the unobserved variable to one of the observed independent variables such as parental death.

Ordinary Least Squares (OLS) regressions may be biased because treatment in an OLS model is endogenous, and thus may misinterpret the effects from other unobserved variables, as an effect of parental death. While controlling for covariates can, for example, account for differences in income among households, controlling for income will not account for unobservables such as the difference in ability of low versus high income households to cope with death, as one is unable to measure variables such as ability. One might hypothesize that a high income household might have a cushion and thus be able to better cope with death, but it is also plausible that a household which loses a high income earner might be ill-equipped to cope with death because it had always relied upon the earning parent, unlike in lower income households, which might not have relied heavily on any one household member.

If one thinks of death as a treatment, an OLS regression may suffer from a selection bias. Households may have been selected into treatment by factors such as dysfunctionality of a family or parents suffering from mental health problems, that also affect a child's educational outcomes. If selection bias does exist, then when one compares treated households (ones which suffered from a parental death) to control households (ones with no parental death loss), one would have a larger representation of dysfunctional households or parents suffering from mental health issues in the treated sample, so the control and treated groups would no longer be balanced. Propensity score matching attempts to balance these two groups as much as possible, by balancing more specifically on observables; one hopes that this fine grain matching also aligns the data on unobservables.

It could also be that parental death has no direct impact on outcomes, but mental illness both increases probability of parental death and also leads to worse outcomes. One might think parental death is causal, but it may just be a spurious correlation, because parental mental illness is unobserved. Such correlations between an observed independent variable and the dependent variable may be incorrect because of the unobserved independent variables. For example, a child who lived in a dysfunctional family and/or with a mentally ill parent may have already been likely to attain fewer years of education than a child in a functional family with a mentally healthy parent, so it would be incorrect for one to conclude that parental death caused the reduction in school grades completed, when in fact it was bound to happen regardless of parental death.

One can attempt to mitigate biases that stems from endogeneity by using a 2-Stage Least Squares (2SLS) regression, which uses an instrumental variable (IV). An IV can be used when both an independent and dependent variable are correlated with the error term, causing omitted variable bias. An OLS model would give biased results in such an instance. An instrument is correlated with an explanatory independent variable, but not with the ultimate dependent variable. In stage 1 of a 2SLS regression, the instrument is used as an independent variable to estimate the variable that was previously endogenous, which in turn is eventually used as an independent variable in stage 2 to estimate the ultimate dependent variable. I do not use an instrumental variable and a 2SLS regression because I was unable to identify any plausible instruments which may cause parental death, but not be correlated with any of my ultimate dependent variables, a child's workforce participation, education, marital status, health, and a household's per capita consumption.

A difference-in-difference (DID) model might be suitable in overcoming biases, but it rests on the strong assumption that the effect of the unobserved variable(s) is time invariant, and that the error term is a fixed constant. However, if effects change or are being multiplied over time, the method does not work. The change in household outcomes between rounds 1 and 2 might be different between treatment and control groups, even if the treatment group had not been treated. The PSM method uses a different approach, based on the idea that if one can create synthetic treatment and control groups and match and balance households in a fine grain way on observables, then one may also be matching and balancing on unobservables.

For the purposes of this paper, I am restricting myself to only variables that theoretically matter in determining one's outcomes, not the demographic variables caste or religion, which do not inherently make someone more likely to lose a parent or determine one's socioeconomic wellbeing. I include caste and religion in the descriptive statistics for both the control and treatment groups, but deem them unnecessary in my regressions because one's religion and caste should not decide one's income, education or health outcomes. Socioeconomic background is captured by other independent variables such as per capita household income in round 1.

VI. Results

I use 0.05 (5%) as my lowest p-value significance threshold, not 10%. Many of my independent variables are significant not just at the 5% level, but also at the 1% and 0.1% thresholds. Only coefficients of significant variables are presented below.

The average treatment effect of the death of a parent across all households (Table 3: PSM (ATE)) causes a child to be 8% more likely to be working, 8% less likely to be enrolled in school, 2% less likely to be married, and results in a child completing 0.34 years less schooling than if a child did not lose a parent. Treatment does not have a significant effect on monthly consumption per capita. A treatment household may already have not singularly relied upon the deceased parent for income, and responsibilities may have already rested on other members, including the children of the household.

The average treatment effect of losing a parent on the treated (Table 4: PSM (ATET)) children results in a child being 6% more likely to be working, 8% less likely to be enrolled in school, 2% less likely to be married, and on average causes a child to finish 0.47 fewer years of schooling than untreated children. One might expect the negative effects of losing a parent to be more acute upon limiting the ATE to only the treated. However, there does not seem to be a big difference between the ATE and ATET. The effect of treatment is still not significant on consumption/capita, nor on education expenditure.

It might seem counterintuitive that parental death causes a child to be less likely to be married. On the one hand, one might assume that a household would more quickly want to bring a daughter-in-law into the household as she could provide a set of helping hands, and more quickly give a daughter's hand away in marriage so that in a country like India, the daughter is not a continuing "burden" or "drag" on the household, as is sometimes claimed. But this phenomenon may be explained partially by the practice of dowry, as a family that is likely to and/or has lost a parent may not be well off, and thus may not yet be able to afford to pay a dowry because of the loss of a/the breadwinner.

The ATE of losing a mother (Table 5: PSM (ATE: Mother Deceased v All Other)) compared to either losing neither parent, or losing a father, is worse. A child is 6% more likely to participate in the workforce, 7% less likely to be enrolled in school, and on average, completes 0.52 fewer years of schooling than those children who have neither lost a parent or lost a father. When a mother dies, a household, on average, also spends almost 2,000 rupees less on a child's education. Mother death does not have a significant effect on consumption per capita, marriage rates, or sickness. The ATET of losing a mother (Table 6: PSM (ATET: Mother Deceased v All Other)) is significant for the same variables and in the same directions as the ATE, except for the ATET of parental death on education expenditure, which is no longer significant. Compared to those children who do not lose a mother, children which lose a mother are 8% more likely to be working, 8% less likely to be enrolled in school, and complete, on average, 0.57 years fewer of schooling.

The ATE of losing a father (Table 7: PSM (ATE: Father Deceased v All Other)), when compared to the sample of children who lose neither parent or lose a mother, is worse. A child is 4% more likely to work, 5% less likely to be enrolled in school, and, on average, completes 0.29 fewer grades of school. The ATET among those who lost a father (Table 8: PSM (ATET: Father Deceased v All Other)) is that children are 5% more likely to work, 7% less likely to be enrolled and complete 0.39 fewer grades of school. The ATET on marital status turns significant, and those children who have lost a father are 3% less likely to be married.

I then restrict my dataset to only the treated households, in order to compare the ATE and ATET for those children who lost a mother with the children who lost a father. The ATE of losing a mother when compared to losing a father (Table 9: PSM (ATE: Mother Deceased v Father Deceased)) is not significant on any outcome variable. The ATET (Table 10: PSM (ATET: Mother Deceased v Father Deceased)) of losing a mother, on the other hand, compared to losing a father, is significant and negative on multiple outcome variables. A child is 9% more likely to be working, 9% less likely to be enrolled in school, completes 0.64 fewer years of school, and is 5% less likely to be married. A household which loses a mother also has 474 rupees less in monthly consumption per capita in round 2.

The ATE of losing a father when compared to losing a mother (Table 11: PSM (ATE: Father Deceased v Mother Deceased)) results in a child completing 0.54 years fewer of schooling, but is not significant on any other variable. Similarly, the ATET (Table 12: PSM (ATET: Father Deceased v Mother Deceased)) results in a child completing 0.96 fewer years of schooling, but is not significant on any other variable.

The last PSM regressions I run include the interaction between my original treatment, parental death, and with a child being female. I do this to measure the difference in outcomes for girls versus boys. Being a girl (Table 13: PSM (ATE: Female Child*Parent Deceased v All Other)) results in 4% lower enrollment in school when treated and a 2% greater likelihood of getting married by the time of the round 2 survey, compared to being a boy. The ATET (Table 14: PSM (ATET: Female Child*Parent Deceased v All Other)) shows an 8% lower likelihood of working and 5% lower rate of enrollment for girls who lost a parent, compared to boys who lost a parent.

The inequality of ATE and ATET across the regressions I run shows that treatment was not really random, and those households who lost a parent were, on average, more likely to lose a parent.

I also run OLS regressions (Table 15: OLS Regressions), which do not control for unobserved heterogeneity. The effect of treatment on school grades completed is negative, as one might expect. Those children who lost a mother are less likely to be enrolled in school and spend less on education than both the control children, and those who lost a father. Girls, relative to boys, are in households with 95 rupees less in monthly per capita consumption. 1,077 rupees less is spent on education, a girl is 3% more likely to be married, and sick 0.13 days more often in the past 30 days. However, a silver lining is that a girl is also 13% less likely to be working, 1% more likely to be enrolled in school, and, on average, completes 0.29 grades more of school.

Parents' education level positively and significantly affects a household's consumption per capita. A child in a rural household is better off than in an urban one, except that s/he is more likely to work than a child in an urban household. Practicing good hygiene and sanitation results in a positive effect on a household's consumption per capita. Counterintuitively, having electricity results in a household spending almost 1,800 rupees less on the education of a child who loses her/his parent, and results in the child, on average, to be 1% less likely to be enrolled in school. The effect of treatment on consumption per capita is not significant. One possible reason why treatment may not be a significant covariate of consumption per capita in round 2 may be that short term consumption is not affected by parental death, because a household which is more likely to lose a parent may already be less reliant on that parent's contribution to the household's consumption needs. However, future consumption may be at risk, because lower school enrollment rates married with greater workforce participation for children who lose a parent may result in worse long term outcomes compared to those children with two parents who stay in school and out of the workforce longer.

It is interesting to compare the PSM results to those from the OLS regressions. The ATE of parental death on a child's workforce participation is 8%, but only 6% per OLS. Children are 8% less likely to be enrolled in school per PSM, but only 6% less likely per OLS. Per PSM, a child, on average, completes 0.34 years less schooling if s/he loses a parent, but 0.52 years fewer per OLS regressions. OLS regressions understate the negative effect of parental death on a child's workforce participation and school enrollment, and do not fully capture the fewer years of schooling a child attains upon losing a parent, when compared to estimates per PSM regressions. Education expenditure and sickness in the 30 days before interview are not significant per PSM, but per OLS, a household spends 1,107 rupees more on a child who loses a parent, and children were sick 0.15 days more in the past 30 days if they had lost a parent. Both PSM and OLS show that parental death leads to a child being married 2% less often than a child with both parents.

VII. Further Research and Shortcomings

Dahejia and Wahba (2016) point out that propensity scores are only as valid as the selection of observable covariates, because relevant unobserved variables may result in biases. While I hope that the control and treated groups are balanced on unobserved variables, I cannot be sure that this is the case. I am unable to include intangibles such as ability, as independent variables. One drawback of the propensity score matching model is that unlike with true randomization, variables which cannot be observed such as preferences and values may cause bias from incorrect attribution. Short of conducting a randomized control trial, the PSM model is a second-best method of balancing the sample on the observable variables.

The University of Maryland and NCAER are working on publishing a third round of interviews with the IHDS households. The length of time elapsed in between the two rounds of the IHDS was as little as 5 years for some households, and as much as 9 years for others. While this data allows me to draw a causal relationship between different independent variables and the observed outcome variables in the short term, I am unable to analyze the medium to long term effects of one-parenthood on a child's outcomes. Das (2016) notes that one-parenthood is not strictly a one-time shock, but rather, a process in which the remaining parent and household members try different strategies over time to adjust and adapt to the shock. Future research on the medium-term lasting effects of parental death can be conducted using the anticipated IHDS-III dataset. To measure long term effects, researchers would have to follow these children over their lifetimes.

Literature has shown that the effect of parental death varies between outcomes for children who are infants and adolescents, versus for those who are teenagers and older. However, I leave it to future researchers to look further into this in the India context. I also do not compare the effect of parental death for those children who lost both parents between the two rounds, with the effect on those children who either lost one parent or no parents. 48 children lost both parents between rounds 1 and 2.

Households which have lost a parent between round 1 and round 2 of the IHDS may have been more likely to drop out of the survey, and the replacement households may not be random nor perfect matches for those who dropped out, so the effects of (possible) parental death in these households may not be captured, and thus the effects of treatment I have found may be understated. One could also look at just the first round of surveys and attempt to estimate the likelihood of a parent dying, and/or the likelihood of a household dropping out of the survey in round 2, as one might imagine a scenario in which those households more likely to drop out may also be the ones more at risk of losing a parent.

There may be a possibility of measurement error in my dataset, as I may be incorrectly estimating deaths. 5.17% of people in my dataset are coded as having died between the two rounds of interviews. Death may be overstated if a parent was coded as dead but in reality did not die, and may have instead left the household. For example, a surveyed woman may have been embarrassed to tell an interviewer that her husband had left her, and a father may thus incorrectly be coded as dead, when really he should have been coded as missing/separated/divorced. The effect of a missing parent on a child may be similar to that of a dead one. I do not isolate the effect of a single-parent household due to parental death versus a single-parent household due to a migrant parent. As Kovac (2017) has shown, the effect of a missing father is large and negative on children's wellbeing outcomes. Further research can analyze the effect on a household of a missing father due to death, versus, for example, a household with a father who is missing because he works in a distant city to support his family, and thus sees his children infrequently.

Parental death may also be overstated because of the types of households more likely to take a long, two-hour survey. Poorer households may have been more likely to agree to answer long surveys because of a lower opportunity cost relative to more well-off households, and thus poorer households, which are correlated with a higher chance of having lost a parent, might be overrepresented in the survey.

I also do not look at the effect of a parent's death on the remaining parent or any other members of the household. It is plausible that the consumption patterns of a remaining parent, grandparent, or other non-own-child household member may change, to try and mitigate any negative effects on a child/children who lost the parent, but this remains to be examined in further research. Similarly to Cosic and Deb's research, my study "is silent on [the] distribution of impacts among surviving individuals in the households."

Future researchers can build upon my work by also analyzing if children get adopted into another household after parental death, and if so, how outcomes of children vary for a) children who did not lose a parent, b) children who lost a parent and were not adopted, c) children who lost a parent and were adopted into another household, and d) existing children in the households that adopt a child who lost a parent.

Even if a child with two parents and a child with a single parent both attend school, the quality of education available to each child may be different, and the quality of job the two children may get hired for in the future may also be different. These factors may also not have been fully captured by my included covariates. Due to unavailability of data, I also did not include variables which could help a household cope with death, such as an extended family or government assistance because of parental death.

I also would have liked to examine any straining of relationships caused by parental death, both within and outside a household. While family often serves as a support system, the child's relationships with other remaining household members may deteriorate. I would have also liked to run ordinal logistic regressions to measure the effect of treatment on the different combinations of workforce participation and school enrollment a child can have.

VIII. Conclusion

Parental death can have significant negative effects on a child in the short, medium and long term. Propensity score matching is a method which, under the right circumstances, helps to reduce potential estimation biases that might arise in measuring such impacts. I use PSM to estimate the effect of parental death on a child's wellbeing outcomes, without needing to randomly assign parental death as a treatment to children. I use the existing IHDS data and estimate the effect of parental death on a child's workforce participation, education, marital status and health, and a household's consumption per capita. I look at the difference in effects from the loss of a mother versus the loss of a father, as well as the difference between effects on girls versus on boys. On average, I find, as one might expect, that parental death leads to worse outcomes on most of my chosen wellbeing indicators, and a parent's death has a larger and more negative effective on a daughter's outcomes than on a son's. I lastly find that a mother passing away, on average, leads to worse outcomes for children on some indicators, while a father passing away leads to worse outcomes for children on other indicators.

IX. Tables

Table 1: Round 1 Summary Statistics, Treatment v Control

Variable	Mean_ Treatment	Frequency	Mean_ Control	Frequency
Age	10.23	26,056.00	8.03	367,726.00
# of People in HH	6.89	17,548.00	6.96	318,712.00
Female	0.40	1,010.00	0.43	19,803.00
Deceased Mother	0.27	685.00	0.00	0.00
Deceased Father	0.75	1,909.00	0.00	0.00
# of HH Assets	11.11	28,282.00	11.54	528,453.00
Main HH Income Source: Hazardous Occup.	0.63	1,602.00	0.62	28,590.00
Mother's Morbidity Scale	0.11	276.00	0.07	3,125.00
Father's Morbidity Scale	0.15	384.00	0.05	2,443.00
Mother Tobacco/Alcohol Use	0.11	276.00	0.07	3,418.00
Father Tobacco/Alcohol Use	0.66	1,686.00	0.55	25,214.00
HH Debt Per Capita	3,457.55	8,802,914.46	2,953.62	135,293,471.37
Mother Age	37.76	96,138.00	32.54	1,490,609.00
Father Age	43.50	110,755.00	37.53	1,719,033.00
Education Level (Self)	3.72	9,461.00	2.72	124,491.00
Mother Education Level	4.24	9,656.00	3.52	137,051.00
Father Education Level	5.47	13,437.00	4.44	192,840.00
Urban HH	0.31	792.00	0.29	13,258.00
Drinking Water Source Within Home	0.49	1,236.00	0.50	23,007.00
Sanitation Index	1.83	4,670.00	1.85	84,920.00
Have Electricity	0.74	1,873.00	0.75	34,167.00
Medical Treatment Available Nearby	0.07	189.00	0.10	4,644.00
Death in HH in Past Year	0.04	92.00	0.04	1,846.00
Monthly Consumption Per Capita	1,300.79	3,311,818.81	1,306.21	59,832,193.84
Religion: Hindu	0.78	1,993.00	0.79	36,390.00
Religion: Muslim	0.14	363.00	0.15	6,671.00
Caste: Brahmin	0.04	91.00	0.04	2,051.00
Caste: OBC or Dalit	0.54	1,387.00	0.56	25,560.00
Caste: Muslim	0.14	359.00	0.14	6,543.00

Note: Frequency for continuous variables is irrelevant.

Table 2: Round 1 Summary Statistics, Treated - Mother Died v Father Died

Variable	Mean_ Mother Died	Frequency	Mean_ Father Died	Frequency
Age	9.49	6,502.00	10.50	20,039.00
# of People in HH	7.26	4,970.00	6.76	12,909.00
Female	0.42	286.00	0.39	743.00
Deceased Mother	1.00	685.00	0.03	48.00
Deceased Father	0.07	48.00	1.00	1,909.00
# of HH Assets	10.81	7,407.00	11.19	21,363.00
Main HH Income Source: Hazardous Occup.	0.69	472.00	0.61	1,157.00
Mother's Morbidity Scale	0.21	141.00	0.07	141.00
Father's Morbidity Scale	0.04	30.00	0.19	358.00
Mother Tobacco/Alcohol Use	0.12	85.00	0.10	200.00
Father Tobacco/Alcohol Use	0.61	417.00	0.68	1,301.00
HH Debt Per Capita	2,338.21	1,601,675.36	3,798.21	7,250,776.39
Mother Age	36.55	25,035.00	38.29	73,097.00
Father Age	41.02	28,096.00	44.50	84,959.00
Education Level (Self)	3.19	2,182.00	3.90	7,436.00
Mother Education Level	3.65	2,178.00	4.45	7,673.00
Father Education Level	5.05	3,272.00	5.61	10,412.00
Urban HH	0.26	179.00	0.33	635.00
Drinking Water Source Within Home	0.47	324.00	0.49	933.00
Sanitation Index	1.77	1,215.00	1.86	3,556.00
Have Electricity	0.73	503.00	0.73	1,403.00
Medical Treatment Available Nearby	0.06	38.00	0.08	156.00
Death in HH in Past Year	0.05	36.00	0.03	62.00
Monthly Consumption Per Capita	1,259.19	862,546.89	1,309.37	2,499,578.16
Religion: Hindu	0.79	542.00	0.78	1,490.00
Religion: Muslim	0.16	109.00	0.14	261.00
Caste: Brahmin	0.04	28.00	0.03	63.00
Caste: OBC or Dalit	0.55	374.00	0.55	1,045.00
Caste: Muslim	0.16	109.00	0.13	257.00

Note: Frequency for continuous variables is irrelevant.

Table 3: PSM (ATE)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATE							
r1vs0.treatment	-2.92	0.08***	-0.08***	-0.34***	139.90	-0.02***	0.14
	(50.71)	(0.01)	(0.01)	(0.10)	(542.98)	(0.01)	(0.09)
N	41126.00	41141.00	41141.00	41117.00	27422.00	41141.00	41141.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: PSM (ATET)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATET							
r1vs0.treatment	26.96	0.06***	-0.08***	-0.47***	850.91	-0.02*	0.29**
	(53.42)	(0.01)	(0.01)	(0.11)	(1096.54)	(0.01)	(0.09)
N	41126.00	41141.00	41141.00	41117.00	27422.00	41141.00	41141.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: PSM (ATE: Mother Deceased v All Other)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATE							
r1vs0.Deceased Mother	-25.51	0.06*	-0.07**	-0.52**	-1994.69***	-0.02	0.07
	(138.79)	(0.03)	(0.03)	(0.19)	(444.56)	(0.01)	(0.14)
N	41112.00	41127.00	41127.00	41103.00	27408.00	41127.00	41127.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: PSM (ATET: Mother Deceased v All Other)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATET							
r1vs0.Deceased Mother	-63.76	0.08**	-0.08**	-0.57**	-726.07	-0.02	0.11
	(95.85)	(0.03)	(0.03)	(0.20)	(871.23)	(0.02)	(0.17)
N	41112.00	41127.00	41127.00	41103.00	27408.00	41127.00	41127.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: PSM (ATE: Father Deceased v All Other)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATE							
r1vs0.Deceased Father	51.28	0.04**	-0.05***	-0.29*	1309.42	-0.01	0.09
	(59.82)	(0.02)	(0.01)	(0.13)	(1623.45)	(0.01)	(0.12)
N	41112.00	41127.00	41127.00	41103.00	27408.00	41127.00	41127.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: PSM (ATET: Father Deceased v All Other)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATET							
r1vs0.Deceased Father	73.26	0.05**	-0.07***	-0.39**	22.20	-0.03*	0.14
	(63.00)	(0.02)	(0.01)	(0.13)	(1699.72)	(0.01)	(0.11)
N	41112.00	41127.00	41127.00	41103.00	27408.00	41127.00	41127.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: PSM (ATE: Mother Deceased v Father Deceased)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATE							
r1vs0.Deceased Mother	-54.93	0.01	-0.06	0.15	-2624.53	-0.02	0.05
	(132.62)	(0.03)	(0.03)	(0.20)	(1494.36)	(0.02)	(0.19)
N	2267.00	2267.00	2267.00	2267.00	1060.00	2267.00	2267.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: PSM (ATET: Mother Deceased v Father Deceased)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATET							
r1vs0.Deceased Mother	-473.81**	0.09**	-0.09**	-0.64**	-759.04	-0.05**	0.26
	(153.28)	(0.03)	(0.03)	(0.24)	(2575.81)	(0.02)	(0.19)
N	2267.00	2267.00	2267.00	2267.00	1060.00	2267.00	2267.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: PSM (ATE: Father Deceased v Mother Deceased)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATE							
r1vs0.Deceased Father	34.23	0.01	0.01	-0.54*	2300.20	0.02	0.02
	(128.80)	(0.03)	(0.04)	(0.26)	(2896.12)	(0.02)	(0.23)
N	2267.00	2267.00	2267.00	2267.00	1060.00	2267.00	2267.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: PSM (ATET: If Father Deceased v Mother Deceased)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATET							
r1vs0.Deceased Father	-149.58	0.04	-0.02	-0.96**	1811.11	0.01	0.07
	(140.24)	(0.04)	(0.05)	(0.32)	(1696.95)	(0.02)	(0.27)

N	2267.00	2267.00	2267.00	2267.00	1060.00	2267.00	2267.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: PSM (ATE: Female Child*Parent Deceased v All Other)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATE							
r1vs0.ftreatment	-92.18	-0.00	-0.04*	-0.16	-664.58	0.02*	0.28
	(71.72)	(0.02)	(0.02)	(0.17)	(548.66)	(0.01)	(0.14)
N	41126.00	41141.00	41141.00	41117.00	27422.00	41141.00	41141.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: PSM (ATET: Female Child*Parent Deceased v All Other)

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
ATET							
r1vs0.ftreatment	-72.45	-0.08***	-0.05*	-0.29	-1138.83	0.02	-0.04
	(91.89)	(0.02)	(0.02)	(0.18)	(718.48)	(0.01)	(0.17)
N	41126.00	41141.00	41141.00	41117.00	27422.00	41141.00	41141.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: OLS Regressions

	Consumption/Capita	Workforce Participation	School Enrollment	Grades Completed	Education Expenditure	Married	Sick Past 30 Days
	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)	b/(SE)
treatment	35.83	0.06***	-0.06***	-0.52***	1107.36*	-0.02**	0.15*
	(43.92)	(0.01)	(0.01)	(0.06)	(534.47)	(0.01)	(0.07)
txdeceasedmother1	-88.65	0.02	-0.05**	-0.08	-2150.63*	-0.02	-0.01
	(82.89)	(0.02)	(0.02)	(0.12)	(1035.15)	(0.01)	(0.14)
Age	53.77***	0.03***	-0.00	1.13***	-649.11***	0.02***	-0.02*
	(6.66)	(0.00)	(0.00)	(0.01)	(73.61)	(0.00)	(0.01)
agesquared1	-2.66***	0.00***	-0.00***	-0.04***	90.47***	-0.00***	0.00
	(0.36)	(0.00)	(0.00)	(0.00)	(4.68)	(0.00)	(0.00)
# of People in HH	-44.81***	0.00***	-0.00***	-0.10***	-210.81***	-0.00***	-0.02***
	(3.07)	(0.00)	(0.00)	(0.00)	(31.25)	(0.00)	(0.01)
Female	-95.01***	-0.13***	0.01***	0.29***	-1077.43***	0.03***	0.13***
	(17.45)	(0.00)	(0.00)	(0.03)	(177.69)	(0.00)	(0.03)
# of HH Assets	93.30***	-0.01***	0.01***	0.12***	594.08***	0.00	-0.01**
	(2.76)	(0.00)	(0.00)	(0.00)	(28.34)	(0.00)	(0.00)
Main HH Income Source: Hazardous Occupation	-24.96	0.05***	-0.03***	-0.03	103.36	-0.01***	-0.05
	(21.08)	(0.00)	(0.00)	(0.03)	(217.45)	(0.00)	(0.04)
Mother's Morbidity Scale	-28.43	-0.01	0.00	-0.15**	59.91	0.00	0.10
	(32.64)	(0.01)	(0.01)	(0.05)	(356.57)	(0.00)	(0.05)
Father's Morbidity Scale	85.32*	-0.02*	0.01	0.04	299.53	0.00	0.16**
	(36.04)	(0.01)	(0.01)	(0.05)	(394.96)	(0.00)	(0.06)
Mother Tobacco/Alcohol Use	-136.22***	-0.03***	-0.04***	-0.23***	730.70*	0.01**	-0.13*
	(31.82)	(0.01)	(0.01)	(0.05)	(366.24)	(0.00)	(0.05)

Father Tobacco/Alcohol Use	-53.31**	0.02***	-0.03***	-0.28***	-896.39***	-0.01***	0.05
	(18.19)	(0.00)	(0.00)	(0.03)	(187.17)	(0.00)	(0.03)
HH Debt Per Capita	0.00**	-0.00*	-0.00	0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Mother Age	6.54*	0.01***	-0.00***	-0.08***	-67.80*	-0.00***	0.02**
	(2.83)	(0.00)	(0.00)	(0.00)	(30.68)	(0.00)	(0.00)
Father Age	-4.19	-0.00***	-0.00	0.00	37.82	0.00***	-0.01**
	(2.48)	(0.00)	(0.00)	(0.00)	(26.82)	(0.00)	(0.00)
Mother Education Level	17.86***	-0.00***	0.00***	0.12***	41.84	0.01***	0.00
	(3.05)	(0.00)	(0.00)	(0.00)	(32.46)	(0.00)	(0.01)
Father Education Level	31.10***	-0.01***	0.01***	0.23***	92.45**	0.00***	-0.01*
	(2.98)	(0.00)	(0.00)	(0.00)	(32.24)	(0.00)	(0.00)
Urban HH	-73.34**	-0.10***	-0.04***	-0.42***	-61.28	0.02***	-0.02
	(22.62)	(0.01)	(0.00)	(0.03)	(235.08)	(0.00)	(0.04)
Drinking Water Source Within Home	-35.17	-0.02***	0.02***	-0.19***	-162.63	0.01**	0.11**
	(19.79)	(0.00)	(0.00)	(0.03)	(205.13)	(0.00)	(0.03)
Sanitation Index	38.10**	-0.03***	0.01***	-0.03	46.68	0.01***	-0.00
	(14.12)	(0.00)	(0.00)	(0.02)	(147.89)	(0.00)	(0.02)
Have Electricity	-81.17***	-0.00	-0.01*	0.36***	-1798.31***	0.01*	-0.25***
	(23.95)	(0.01)	(0.00)	(0.03)	(254.07)	(0.00)	(0.04)
Medical Treatment Available Nearby	-72.34*	-0.03***	0.02***	0.08	-344.38	0.00	0.30***
	(29.52)	(0.01)	(0.01)	(0.04)	(283.07)	(0.00)	(0.05)
Death in HH in Past Year	-33.68	0.02	-0.01	-0.14*	-90.33	-0.00	0.01
	(44.51)	(0.01)	(0.01)	(0.06)	(457.13)	(0.01)	(0.07)
Monthly Consumption Per Capita	0.30***	-0.00	0.00***	0.00***	1.45***	-0.00	0.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)
Constant	423.10***	0.11***	1.02***	1.45***	-165.02	0.92***	1.39***
	(63.22)	(0.01)	(0.01)	(0.09)	(670.60)	(0.01)	(0.11)
R-Squared	0.20	0.29	0.41	0.61	0.16	0.22	0.01
N	41126.00	41141.00	41141.00	41117.00	27422.00	41141.00	41141.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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