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Piped Water Access, Child Health and the Complementary Role of Education: Panel Data Evidence from South Africa



UNIVERSITY OF THE
WITWATERSRAND,
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Abstract:

This study establishes the causal impact of piped water access on child health in rural South Africa (2008 – 2015) through the use of a panel dataset and a quasi-experimental sample space. By employing an ordinal measure of child health as the dependent variable within ordinal probit, fixed and random effects, propensity-score matched difference-in-difference and system-GMM estimators, it is demonstrated that positive health benefits for children with access to piped water are observed if and only if the minimum level of educational attainment of the primary-caregiver is equal to or greater than 7 years. This finding of complementarity is demonstrated to be a function of an individual's (in)capacity to evaluate water quality: people below this threshold suffer from a piped water bias, place insufficient weight on the observable characteristics of water when determining water quality and are subsequently less likely to treat piped water preceding consumption. The interactional effect estimates are statistically significant at the 5% level with the impact ranging from 1.617 to 2.008 levels.

TABLE OF CONTENTS

LIST OF TABLES ……pg. 4
LIST OF FIGURES ……pg. 5
INTRODUCTION ……pg. 6
LITERATURE REVIEW ……pg. 9
Relevance ……pg. 9
Empirical Studies ……...pg. 11
DATA AND DESCRIPTIVE STATISTICS ……...pg. 16
Primary Data ……...pg. 17
Variable Discussion ……...pg. 18
Descriptive Statistics ……...pg. 20
Supplementary Data ……...pg. 22
Variable Discussion ……...pg. 23
Descriptive Statistics ……...pg. 23
ECONOMETRIC METHODOLOGY ……...pg. 24
Model I ……...pg. 24
Model II ……...pg. 26
Model III ……...pg. 27
Model III-I ……...pg. 29
Model III-II ……...pg. 31
Model IV ……...pg. 31
Limitations ……...pg. 34
RESULTS ……...pg. 34
Robustness Checks ……...pg. 39
Discussion ……...pg. 42
CONCLUSION ……...pg. 48
REFERENCE LIST ……...pg. 50
APPENDIX ……...pg. 56

LIST OF TABLES

Table 3.1: Summary Statistics of Household and Locality Characteristics (Panel Weighted; Rural) ……pg. 20

Table 3.2: Summary Statistics on Individual Characteristics (Panel Weighted; Rural) ……pg. 21

Table 3.3: GHS Summary Statistics of Individual Characteristics (Sample Weighted; Rural) ……pg. 23

Table 5.1: Child Health Model Outputs ……pg. 37

Table 5.2: Child Health Model Interaction Outputs ……pg. 38

Table 5.3: Child Health Model Interaction Outputs - Robustness Check ……pg. 41

Table 5.4: Determinants of Treatment ……pg. 44

Table 5.5: Determinants of Perceived Water Safety ……pg. 45

Table 8.1: Summary Statistics on Household and Locality Characteristics (Panel Weighted; Rural) ……pg. 54

Table 8.2: Description of Explanatory Variables ……pg. 55

Table 8.3: Summary Statistics on Care-Giver Education Strata (Sample Weighted; Rural) ……pg. 56

Table 8.4: GHS Summary Statistics on Household, District and Regional Characteristics (Panel Weighted; Rural) ……pg. 56

Table 8.5: Parallel Lines Assumption Testing Results at the 0.05 Level of Significance ……pg. 57

Table 8.6: Forward Stepwise Logit Outputs ……pg. 57

Table 8.7: PS-Matching T-Test Results – Logit ……pg. 57

Table 8.8: PS-Matching T-Test Results – Kernel ……pg. 58

Table 8.9: System-GMM Diagnostics ……pg. 58

LIST OF FIGURES

Figure 3.1: Mean Child Health by Period and Water Access ……pg. 22

Figure 4.1: Propensity Score Overlap ……pg. 30

Figure 5.1: Treatment of Water Perceived of as Unsafe
by Educational Attainment Cohort ……pg. 43

Figure 5.2: Weight of Determinants of Perceived Water Quality ……pg. 46

Figure 8.1: Relative Coefficient Weight in Determining
Water Safety: Clarity of Water ……pg. 59

Figure 8.2: Relative Coefficient Weight in Determining
Water Safety: Odor of Water ……pg. 59

Figure 8.3: Relative Coefficient Weight in Determining
Water Safety: Taste of Water ……pg. 60

1. INTRODUCTION

Access to clean and safe drinking water is a self-evidential necessity for ensuring the healthy growth and development of children. This is in part due to a child's decreased natural immunity to illnesses and environmental factors which incurs a higher probability of suffering from water transmitted diseases and ailments (Adewara & Visser, 2011). In 2016 the World Health Organisation estimated that 361 000 children under the age of 5 and mostly located in developing countries perished from diarrhea (WHO, 2016a). In recognition of its importance both the United Nations and the South African Government guard access to clean and safe drinking water as a fundamental human right. Through empirical analyses, this paper identifies that regardless of a public commitment to this goal, piped water access in South Africa does not in and of itself ensure that positive health benefits are experienced by child consumers - a minimum level of educational attainment of the primary caregiver serves as a necessary complementary condition to guarantee that health benefits are observed in the presence of access to publicly distributed water.

Access to piped water is a potential mechanism for ensuring that publicly provided water is of a minimum standard of quality and is fit for use. Yet water-infrastructural as well as individual-specific behavioural factors may alter the quality of water preceding consumption which may in turn lead to negligible health impacts for children. The public costs associated with poor health induced by low quality water can be substantial and are borne disproportionately by the poor: during 2006, inadequate sanitation and water access incurred economic losses associated with health spending, declines in productivity and labour diversions totalling $28.4 billion a year or 5% of continental GDP in Sub-Saharan Africa alone (UN, 2006). Within the South African context, it is estimated that 20% of deaths in children under the age of 5 are the result of diarrhea – a particularly prevalent ailment associated with the consumption of contaminated water (Chola, *et. al.,* 2015). The financial and social costs incurred by poor water quality therefore necessitates appropriate analyses be undertaken to determine the conditions under which improvements in health status and the avoidances of child deaths can be ensured when access to superior water sources is provided.

The South African context is unique for an analysis of this nature due to its history: Apartheid inherited water infrastructure required significant expansion in access to account for the historical racial and spatial inequalities associated with a dual-tier economic system (Earle *et. al.*, 2005). The

burdens associated with this demand have contributed to instability and fluctuations in water supply as well as heterogenous quality throughout the country (Agenbag & Balfour-Kaipa, 2008; SAHRC, 2014). At present, no robust, nationally representative analysis of this nature have been conducted for the South African circumstance.

Cross-country empirical studies have established a general argument in favour of access to piped water as beneficial for child health and have alluded to the role of the educational attainment of the child's caregiver as an enabling factor. Jalan & Ravallion (2001) seminal paper estimated a fall in diarrhea prevalence of 21% in rural India for children under the age of 5 years who have access to piped water. The authors furthermore established the aiding role of the educational attainment of the primary care-giver. By employing propensity score matching estimators, structural differences between the treatment and control were accounted for although the cross-sectional nature of the data failed to illustrate dynamics nor account for time-invariant omitted variables. Galiani & Gertler (2005) confirmed a reduction in the frequency of child mortality induced by water born ailments due to improvements in water quality in Argentina. Conducted through a propensity score matched difference-in-difference approach, the paper established that the privatisation of public water supply from the public sector led to increases in water quality, reducing child morbidity. This was conducted with community level variables which overlook the role of individual specific effects. The range of estimates in the literature demonstrate that the country-specific contexts associated with water quality standards and distribution processes lead to limited external validity. As such, best-practice would suggest pursuing analyses on a country by country basis. It is proposed that studies to date have made inadequate efforts at employing methods that collectively and within a single framework account for self-selection and/or employ exogenous instruments, leverage panel data methods as well as establish the conditions required to ensure health improvements for children in the presence of piped water.

The following paper employs an impact evaluation methodology to demonstrate the conditions necessary to ensure that access to piped water improves child health in rural South Africa during the period of 2008 to 2015. Both a pooled-cross sectional and a panel-data set are made use of allowing for more robust analytics. The methodology and results establishes an argument for causality through a range of models including ordinal probit, fixed and random effects, propensity-score matched Difference-in-Difference, and system Generalized Method of Moments. The complementary relationship between educational attainment and water source type is core to the analysis: a threshold, minimum level of educational attainment of the primary care-giver is hypothesised as a necessary

complementary effect to ensure that positive health gains are experienced by a child with access to piped water. This level is confirmed as statistically significant at 7 years.

In addition to being the first analysis of this nature in the South African context, the study is novel by contributing to the existing literature by establishing a necessary educational complementary effect to piped water access. The educational effect is estimated as a function of a specific number of years of education. The third addition is explaining the mechanisms through which the primary care-giver's educational attainment functions to positively influence the health impacts of piped water access for a child under their care. This tier of analysis demonstrates that the educational attainment threshold is a function of an individual's bias towards assuming piped water as safe, regardless of the observable characteristics of the water. This bias decreases an individual's capacity to accurately perceive the quality of water and subsequently depresses the likelihood of pre-consumption treatment. The process would in turn impact the health of the child under their care should the water be contaminated and be consumed without adequate treatment.

The paper is structured as follows. Section 2 contains a literature review. The review outlines global and South African trends in piped water access, the role of water in an individual's health and the key findings of similar empirical studies. The section assists in making apparent that this paper's methodologies, results and datasets used are innovative. Section 3 discusses the data and descriptive statistics of both datasets employed in the study. The econometric methodology is outlined in Section 4. Through identifying the strengths and weaknesses associated with each of the 4 models employed, an argument for causality is established. Current econometric limits pertinent to the structure of the variables and the data employed in the study are discussed. Section 5 contains the results of the analysis. All models have a total of 13 specifications. Each specification employs an interaction between piped water access and a dummy measuring the minimum level of educational attainment achieved by the primary care-giver. The interaction term increases by one year of education in each specification seeking to establish a minimum and necessary threshold required to ensure statistically significant health benefits are observed. The discussion component of this section explains how behavioural responses to water are impacted by the level of educational attainment and is the mechanism through which educational attainment interacts with piped water to impact child health. Section 6 concludes.

2. LITERATURE REVIEW

A rich body of literature exists regarding the role of piped water in child health and the econometric efforts pursued when attempting to quantify these effects. The following literature review demonstrates the relevance of the study as well as outlining the key findings and methodologies of other studies with a similar focus area.

2.1. Relevance

Publicly provided piped water offers a potential avenue for increasing the likelihood that water is safe for consumption by ensuring that treatment occurs preceding use. Strict limits on the improvements in quality exist as the quality of piped water at point of use can only be as high as that of point of entry, with a potential for deterioration during the process of distribution (Shaheed *et. al.* 2013). The deterioration in quality is a function of a number of factors including but not limited to: a lack of sufficient centralised treatment; intermittent supply of water due to electrical outages and pump failures leading to within-system stagnation; supply stoppages increasing the likelihood of water storage, the facilities of which may be inadequate or unclean which enables the seeding of bacteria; poor operation and maintenance of treatment plants, and; bursts and leakages in piping systems that leads to contamination by environmental factors (Shaheed *et. al.* 2013; Jagals, 2012). The system therefore has the possibility of generating negative externalities, as ailments are potentially contagious. Piped water may therefore be assumed by the consumer to be safe when the opposite is in fact true.

The provision of piped water access offers a multitude of benefits for a household. By reducing the distance of a household from source of its water, piped access is a mechanism that improves not only water quality but also quantity by reducing the efforts required for transportation and storage. This reduction in distance decreases the likelihood of contamination induced by the use of poor water storage facilities. Furthermore, increased time savings have been identified by Hutton (2012) as a significant component of the total economic benefits incurred by improved access. This may subsequently reduce the opportunity cost associated with the time required to treat water preceding consumption leading to an increased likelihood of treatment. This outcome is particularly valuable as the WHO (2012) identified that treatment at point of use is the most cost-effective mechanism for improving water quality. The time savings obtained may increase the time available to be dedicated to the pursuit of other household and individual activities that are health promoting. Improved access to water furthermore decreases the marginal value of the water due to its ready availability and may increase the likelihood of it being used more constructively and generously and

not reserved solely for consumption. Regardless of these opportunities, consumption and use of piped water may offer negligible or even detrimental health benefits in the case that the piped water is not of a superior quality to alternative sources (Adewara & Visser, 2011; Lechtenfeld, 2012). An absence of pre-consumption treatment under the assumption of the superiority in quality of the piped water source may compound this effect.

The right to sufficient water is guarded by the constitution of the Republic of South Africa (Republic of South Africa, 1996)[1]. Following democratisation in 1994, substantial strides in the expansion of access to publicly provided water sources for the greater South African population have been made. The inheritance of a dual-tier economic system posed significant challenges as the majority of the population were without sufficient access to necessary infrastructure and public goods: Apartheid-regime investments were geared towards furthering the development of the ruling minority (Earle *et. al.* 2005). These racial inequalities incorporated a spatial component as the estimated 12 to 14 million people without access to a formal water supply in 1994 occupied predominantly rural, 'homeland' areas (Earle *et. al.*, 2005). Due to the dispersed and low-density nature of rural populations, expansion in water supply to these communities is costly and logistically problematic and at times beyond the means of many developing governments leading to the provision of communal taps (Zwane & Kremer, 2007).

The Department of Water Affairs and Forestry (DWAF) estimated that in 2007, 94% of the population had access to basic water infrastructure – a rise from 48% in 1994 (DWAF, 1999)[2]. Agenbag & Balfour-Kaipa (2008) identify that although aggregate national improvements are significant, there remain a select number of municipalities with persistently poor safe water provision whilst certain localities have suffered from a deterioration in water quality. This fall in the standards of publicly provided water has been the result of insufficient investment in and maintenance of treatment facilities and infrastructure (Agenbag & Balfour-Kaipa, 2008). The DWAF is empowered to set the standards of water quality through establishing metrics for physical, chemical and biological contaminants (DWAF, 1996). Mackintosh *et. al* (2004) estimated that in 2004, only 43% of South African municipalities provided water that was consistent with these standards. These findings are echoed by the South African Human Rights Commission which comment on a report released by the

[1] 'Sufficient water' is interpreted by the South African Human Rights Commission as referring to water of an adequate quality and quantity to satisfy household needs (SAHRC, 1999).
[2] The accuracy of these figures is questionable and may be inflated due to political interests and soft definitions.

Department of Performance and Monitoring that water services in 9% of South African municipalities, "were in a crisis state, with an acute risk of disease outbreak" (SAHRC, 2014:13) and that 38% were considered 'high-risk' and on the threshold of sliding into crisis status. Disparities in access and quality continue to be regionally and spatially heterogenous in South Africa (SAHRC, 2014). The vulnerable cohorts of society are most likely to suffer due to these shortfalls. Chola *et. al.* (2015) estimate that 20% of deaths in South African children under the age of 5 are the result of diarrhoea, illustrating the potentially detrimental impact of poor water quality sources on child health.

The process of treatment is a potential guard against the consumption of sub-quality water. Biases towards the assumption that piped water access is safe to consume regardless of treatment may pose a threat to the wellbeing of a household by decreasing the probability of pre-consumption treatment. Within the South African context, these biases may be substantial as public perceptions of the quality of piped water are potentially influenced by government opinions. A public statement by the Institute of Waste Management of Southern Africa maintained that South Africa is one of 12 countries on the globe whereby the consumption of tapped water is safe and that said water is ranked the third best in quality (Rademeyr, 2013). This was echoed by a speech by president Jacob Zuma in 2013. These statements are argued by Rademeyr (2013) as false. The public statement draws into question the validity of the source of information and is perturbing insofar as a viable, unified global index for water quality does not yet exist. The informational diffusion of such a statement and its capacity to influence household behaviour is potentially damaging for general child health should it depress the incentive to treat piped water preceding consumption. This is especially true considering the findings of Wright *et. al.* (2012): perceptions of drinking water safety in South Africa were established as a function of odor, clarity and taste, as consistent over time and uninfluenced by a cholera outbreak during the period studied. The paper further verifies that piped water is, on average, considered superior in quality and safer to drink than other sources. Individuals may therefore overlook the existence of potential contaminants in publicly provided water and dedicate inadequate effort and resource to water treatment from these sources under the belief that the water is safe.

2.2. Empirical Studies

A review of the literature demonstrates that a rich array of methodologies have been employed to establish a statistically significant relationship between water source type and child health, concluding in the majority of cases that piped water access improves child health after controlling for household, district and individual level characteristics. Due to the country-specific nature and quality

of publicly provided water, external validity in all cases is questionable and is cause for the wide range of results observed. It may therefore be argued that the most effective means of understanding the domestic impacts of piped water access on child health are offered by the use of domestic data. Waddington *et. al.* (2009) identify that variables relating directly to context and external validity include location and season of study, water supply and sanitation baselines as well as study length and sample size. Panel data methods allow for the time invariant contextual impacts to be controlled for, leading to more accurate estimates.

A meta-analysis conducted by Esret *et. al.* (1991) evaluated the health based impacts of water and sanitation through the study of the findings of 144 papers. The authors disaggregate their measures between the methodologically rigorous papers which include a measure of statistical significance and otherwise. A wide range of metrics and dependent variables are identified and include the prevelance of diseases and ailments associated with water and sanitation that are more common to developing countries. The authors establish that between 1966 and 1986 a median reduction in child morbidity associated with improvements in water and sanitation for diarrhea, trachoma and ascariasis are substantial, at 26%, 27% and 29% respectively. With regards to water access specifically, analyses that measure the impacts of both water quality and quantity are demonstrated to be positive for child health.

A more recent systematic overview of the existing literature is conducted by Waddington *et. al.* (2009). The meta-regression reviewed 71 impact evaluations of water based programs and their capacity to reduce child diarrhea. The analyses spanned 35 developing countries over 30 years and covered 130 000 children, establishing the impacts associated with water supply and quality improvements, increased sanitation and hygiene programs. Stringent inclusion criteria were set necessitating studies control for endogeneity of program self-selection.

A number of important conclusions can be drawn from the Waddington *et. al.* (2009) paper regarding the capacity for each of these programs to generate a tangible health benefit: point of use interventions in water quality are superior to those that introduce improved supply sources or implement source treatment[3]. As such, the role of the individual and their behavioural response to water is key to ensuring that positive health gains are achieved as there are limits to the degree to which the public sector can guarantee the quality of water supplied. Drawing on diffusion theory, the

[3] Improved sources include a household connection, public standpipe, borehole, a protected dug well, a protected spring or rainwater collection.

authors maintain that preventative measures such as treatment at point of use have a slower rate of uptake as the benefits are difficult for the program participant to observe directly. Consequently a number of users discontinue what was communicated in educational programs due to the perceived costs outweighing the benefits, inhibiting the positive health gains potentially offered. Household, individual and community level characteristics come to establish the context within which an individual operates and influence the effectiveness of program intervention. As a result, "behavioural mechanisms, the beliefs, values and experiences of the treatment population and the socio-economic environments are important determinants of the adoption and sustainability of interventions" (Waddington, *et. al.,* 2009:15), necessitating these variables be sufficiently controlled for and investigated within the framework of appropriate counterfactuals and systems which purge time-invariant influences.

As a result of potential structural differences in characteristics between groups with piped water access and those without, appropriate statistical measures need account for self-selection bias. Jalan & Ravallion (2001) employ a propensity score matching estimator to measure the prevalence and duration of diarrohea in rural Indian children under the age of 5 years. The pooled cross-sectional analysis confirms the positive benefits associated with piped water access, leading to falls in diarrhoea prevalence and duration by 21% and 29% respectively (Jalan & Ravallion, 2001). Through stratification the authors illustrated that there are no statistically significant positive child health benefits for the bottom two income quintiles for households with piped water access. By estimating interactions with the piped water variable, it was established that a child whose mother has an educational attainment above that of a primary level would ensure a reduction in the prevalence and duration of diarrhoea. Although not in interaction format, Fink & Gunther (2010) demonstrate that the educational attainment of a mother has a substantial impact in reducing the prevalence in child diarrhea. These studies establish the role of caregivers in ensuring the wellbeing of a child: more educated individuals are aware of the necessary precautions that need be taken when presented with water of a questionable quality in terms of both treatment and storage (Diaz & Andrande, 2015).

Establishing a causal relationship between piped water access and child health can be obtained through the use of instrumental variables. By instrumenting for piped water access with both the distance from the city centre and a measure of how penetrable the ground is, Lechtenfeld (2012), confirmed that the provision of piped water in urban Yemen lead to an increased prevalence of diarrhoea in children. All OLS and Probit models are consistent in this result with the author finding

that the negative impact is a function of public water rationing which induces intermittency in supply and increases pollutants. The detrimental affects are compounded by the need for households to store water, the facilities of which may be unhygienic and subsequently deteriorates the quality of the water. Interestingly, boiling and filtering of water is found to have no impact on the prevalence of diarrhoea, though the author suggests that this finding may be the result of poor statistical power due to a limited sample size. Kremer *et. al.* (2006) have similar findings, illustrating that, "access to sanitation or hygiene knowledge before an improved water supply program does not appear to enable households to better translate quality improvements in source water into… health improvements in their study region in Kenya" (Zwane & Kremer, 2007: 20).

A range of dependent variables is made use of in the literature due to the wide variety of impacts on child health that water source type can cause. Anthropometric measures capture the capacity of water source type to alter a child's rate and quality of growth. Adewara & Visser (2011) employ an OLS estimator to confirm that Nigerian children below the age of 5 years with piped water access experience gains in height Z-scores[4]. Access to borehole water is demonstrated to offer a larger benefit as well as improvements in weight Z-scores. Probit regressions illustrate that the likelihood of stunting is decreased if water is sourced from a borehole. The authors suggest that the superiority in outcomes associated with borehole water is potentially the result of poor public sector treatment of piped water preceding distribution. Furthermore, parent educational attainment as an independent control variable leads to positive health outcomes for the child and is significant in all specifications at the 1% level.

The shortfalls of publicly provided water are established again in Galiani & Gertler (2005) who implement a propensity score matched difference-in-difference (DiD) methodology to measure the impact of privatisation of local water service on the mortality of Argentinian children below the age of 5. The private sector's operations were seen to reduce child deaths associated with water specific infectious and parasitic diseases with a range of 3.2% and 18.2%. Panel data methods allowed the authors to purge time-invariant characteristics such as perceptions of water quality and context that might otherwise have biased results Within this study, the private sector can be deemed as more efficient than the public, translating into expanded access and quality. The privatisation process

[4] Height Z-scores measure the cumulative health of the child. In contrast, weight z-scores are a more contemporaneous measure of wellbeing (Diaz & Andrande, 2015).

overcame the potential negative health benefits that may result from profit-maximising incentives that would otherwise lead to the supply of sub-quality water in the pursuit of reducing costs.

A wide range of household level factors have the capacity to impact child health and is illustrated by an array of statistically significant covariates within the literature. Water, sanitation and hygiene are commonly grouped together in discussions of water based impacts on health, the significance of which being that improved human waste removal and hygienic practices lead to increased wellbeing, regardless of piped water access. Diaz & Andrande (2015) employ OLS and district level fixed effects to measure the impact of piped water and sanitation on child diarrhea prevelance and nutritional status in Peru. The pooled cross-sectional study contains an interaction between sanitary identifiers (such as the existence of a flush toilet) and piped water access as well as additional covariates regarding the mother, head of household, and district characteristics. The complementary effect between improved sanitation and water source is demonstrated as statistically significant and remains when a dummy measuring whether the household boils water preceding consumption is introduced. As such, regardless of treatment preceding consumption, improved water and sanitation lead to health gains.

On average, analyses of the impact of water and sanitation on child health have failed to combine a number of necessary methodological requirements within a single framework to infer a robust and causal findings. Studies should seek to employ both appropriate counterfactuals and sufficient sample size that spans across an extended time frame which would account for cumulative effects. In addition, analyses would benefit further by employing panel-data methods which account for individual time-invariant characteristics. Finally, insufficient effort has been made to precisely determine the conditions necessary for ensuring positive child health benefits accompany piped water access nor understand the mechanisms through which the educational attainment of the primary care-giver influences health outcomes.

The following paper provides a number of contributions to the existing literature. To the best of the author's knowledge, this study is the first to robustly and econometrically establish the conditions under which access to piped water can positively impact child health in rural South Africa. The estimates are conducted within a panel-data structure, allowing for superior methods of impact evaluation by accounting for both individual and household specific dynamics as well as the impact of time-invariant unobservables.

As demonstrated by previous studies, the educational attainment of the primary-caregiver has the potential to influence the health of children with piped water access. A key level of educational attainment for the primary care-giver has been hypothesised and confirmed as a necessary complementary effect to piped water access. This minimum level has a bandwidth from 7 to 9 years of formal educational attainment, beyond which health based benefits for children with access to piped water are guaranteed. Below this level no statistically significant impacts on child health exists and is evidence that piped water access in and of itself does not improve child health. When reviewing the available literature, the process of disaggregating educational attainment of the primary care-giver by year is currently untested.

A wide range of estimators are made use of within the study to demonstrate a causal relationship and isolate the impact of intervention. These include that of system Generalized Method-of-Moments[5], ordinal probit, fixed and random effects as well as propensity-score matched Difference-in-Difference. A further contribution is the parallel use of a secondary dataset to unpack the key findings: through stratification of the analysis by levels of educational attainment, group level variation in the likelihood that an individual treats piped water preceding use is established. It is demonstrated that the threshold level of educational attainment required to ensure that child health improves with piped water access is in part a function of an individual's capacity to evaluate water quality. Individuals above the threshold level of education place greater weight on observable characteristics of the water, are less likely to assume piped water to be safe regardless of these characteristics and are subsequently more likely to treat the water preceding use. It is confirmed that a structural break in the proportion of weight granted to water source type and observable characteristics in the determination of water quality exists at the 7 year of educational attainment level – consistent with the core findings of the paper.

3. DATA AND DESCRIPTIVE STATISTICS

Two sources of data have been employed in the study. Section 3.1 outlines the primary dataset analysed in the modelling process which is used to identify the key results of the paper Within the primary dataset, a full sample and a quasi-experimental sample are made use of. Section 3.2 outlines the secondary dataset used to supplement and provide a richer understanding of the core findings. Due

[5] To the best of the author's knowledge, this has not been yet been attempted in this field of study.

to the existence of a total of 3 samples, the descriptive statistics of the quasi-experimental sample space are contained in Table 8.1 in the appendix.

3.1. *Primary Data*

Data used in the primary analysis is drawn from the National Income Dynamics Study (NIDS) of South Africa. Overseen by the Southern Africa Labour Development Research Unit (SALDRU), the panel-dataset contains individual, household and derivable district level variables sampled over four periods with approximately 2 year intervals. The individual level questionnaires are disaggregated between children and adults, the latter thus containing data regarding the primary care-giver. A total of 29 733 core sample members were tracked from 2008 to 2015, allowing for analysis into key changes in peoples' experiences of, "employment, inequality, health and wealth, as well as the effects of social spending such as education" (Chinhema *et. al.*, 2016:6).

The NIDS survey design is conducted through primary sampling units (PSU's). National representation of the sample was achieved by determining the probability of a member being surveyed on the basis of geography. Individuals are thus weighted in accordance with this probability, correcting for potential over or under-concentration of observations within a certain locality (Mohadjer *et. al.*, 2013). All standard errors in the analysis have been clustered at the PSU level to ensure a robustness in results. This prevents unrealistically small standard errors by avoiding potential serial correlation induced bias between individuals - evidence of a lack of independence across observations. (Adewara & Visser, 2011; Angrist & Pishcke, 2008).

The NIDS dataset contains panel weights to account for systematic non-response and attrition that would otherwise result in some cohorts of the population with specific characteristics being misrepresented. As stated by the NIDS guide, "individuals who were successfully re-interviewed… are not a random subset of all individuals interviewed in the first wave" (Chinhema *et. al.*, 2016: 62). This justifies SALDRU's implementation of a probit model for use as a panel weight to estimate the likelihood of an individual remaining present through the survey periods. To avoid the potential for erroneous results due to extreme panel weights, SALDRU trimmed values at the 1st and 99th percentiles of the weight distribution (Chinhema *et. al.*, 2016). These panel-weights are employed as sample probability weights throughout the analysis to ensure that the outcomes are nationally representative.

3.1.1. Variable Discussion

The full NIDS sample has been reduced to contain observations on individuals relevant to the study: analysis concerns children who occupy rural household up to and including the age of 15 years[6] [7]. Additional data regarding each respective child's household and care-giver characteristics is included. A total of 4818 individuals comprise the sample in the initial period. A complete description of all variables is contained in Table 8.2 in the appendix.

In contrast to the adult level questionnaire which contains a battery of variables regarding specific health based outcomes, the child level measure of health is ordinal with 5 levels of perceived health status. This ranges from a high of 'Excellent' to a low of 'Poor'. The potential for measurement error due to the subjective nature of the variable is apparent, yet insofar as the measure is employed as the dependent variable, attenuation bias is of no concern. It is assumed that should measurement error in health status exist, it is random in nature and not a function of measurable characteristics. The broad nature of the measure comprises all factors which determine an individual's general health and confirms the validity of the variable due to the range of impacts that the quality of water might have. The significance of this rests on how health-related outcomes associated with water quality not only incorporate impacts specific to the gastro-intestinal tract (such as the prevalence of diarrhoea and painful urination), but also one's general propensity for illness and a child's height and weight z-scores[8]. Due to the contemporaneous nature of the measure, recall bias induced inaccuracy is of no concern.

The treatment variable is drawn from the household-level questionnaire which establishes water source type based on 11 options. This treatment variable, *Pipe,* is in dummy format and captures if a household draws water from a piped tap. The tap may be located within the household, within the property limits or publicly available to the district. In accordance with Fink & Gunther (2010), these options are considered technologically superior.

The continuous educational attainment variable of the primary care-giver was created by collapsing all individual level data regarding the period of formal educational in primary, secondary

[6] A rural household is defined as one that exists in either a 'Traditional' or 'Farm' geographic type. The prior is, "district owned land under the jurisdiction of traditional leaders" (Chinhema *et. al.*, 68 : 2016) and the latter, "land allocated for and used for commercial farming, including the structures and infrastructure on it" (Chinhema *et. al.*, 68 : 2016)

[7] The study's definition of a child is consistent with the NIDS definition based on age.

[8] Bivariate regression estimates confirm the relationship between specific ailments and the dependent variable, validating its use. Child height and weight z-scores are both correlated with perceived health status at the 1% level. The presence of diarrhea is estimated as impacting adult perceptions of health status, also at the 1% level.

and tertiary institutions[9]. Thereafter a vector of dummies was created which measure whether the individual has achieved at least a certain standard of educational attainment. This vector increases from 1 to 12 years or more with an increment of 1 year[10]. Descriptive statistics regarding the distribution of educational attainment within these cohorts is contained in Table 8.3 in the appendix. Potential strategies to eliminate missing observations in the educational attainment variable were tested and rejected on theoretical grounds[11].

Further controls include real monthly district and regional incomes[12]. Regions are defined at the cluster level, comprising 400 different areas. Districts are broader and categorised into 54 areas. These serve to control for the possibility of superior health status in more affluent communities and regions whereby municipalities have a larger tax base to draw from and allocate to the provision of public goods. The aggregate educational attainment for each of these levels controls for knowledge diffusion and learning processes regarding appropriate water treatment and hygienic practices that are better understood by a higher educated district or region. The combination of these two levels accounts for the localised and more macro level effects of education and earnings and reduces the potential for omitted variable bias in the treatment variable should these variables be correlated with piped water access. These area identifiers are constant through time and contribute to control for the role of context. Household level aggregate educational attainment and real monthly income are also estimated to capture similar effects: more affluent households have more resources to dedicate to the care of a child whilst more educated households are better equipped to ensure health promoting activities are pursued. The household level measure of education concerns adults only.

Proxies for the quality of municipal governance and the existence of publicly provided goods control for potential heterogeneity in piped water quality and are captured in whether the municipality collects refuse at least once a week. This variable has a dual function in furthermore accounting for the external sanitary state of the household/district. This indicator functions in conjunction with a

[9] South African children enter their first year of primary school in Grade 1, generally at the age of 7 years. Children usually leave primary school at the age of 14 to enter high school in Grade 9. High school is completed after grade 12, generally at the age of 18 years.

[10] The vector of dummies is described as follows: a value of 1 is allocated to an individual that has achieved at least X years of educational attainment and 0 if otherwise. X ranges from 1 to 12.

[11] Processes include: imputing missing values as a replica of the most recent available observation from preceding sample periods, and; application of the mean value of educational attainment for an individual drawn from all available observations of education attainment for that individual. These options were deemed inadequate insofar as a number of care-givers may be actively pursuing continued education.

[12] All nominal earnings related variables have been reweighted with country level CPI employing 2010 as the base year. The data is sourced from the World Bank Development Indicators Dataset (2016).

variable that establishes whether the household uses electricity to cook and is a measure of the nature in which food is prepared as well as being directly correlated with electricity access[13]. The potential for a positive bias of municipalities towards providing superior public goods and infrastructure to metropolitan areas is captured by a dummy identifying whether the household exists in a metropolitan area. A dummy that identifies the existence of a quality toilet in the household as per Diaz & Andrande is included to measure the state of sanitation in the household (2015)[14].

The number of children overseen by each care-giver serves to account for the potential intensity with which a child is cared for. A higher ratio decreases the time and resources available to be dedicated by the primary care-giver to each individual child. Alternatively, a higher ratio may incur a fall in child health status due to the greater potential of disease and pathogen transmission within the household, akin to the household size variable commonly used in other studies (Lechtenfeld, 2012). The nature of the relationship between the child and primary caregiver is accounted for by a dummy measuring whether the primary care-giver is a parent. This captures the potential for increased effort in care of a child on the basis of proximity of relations. Within the South African context, the high frequency of rural-urban working migrants and the death of many parents results in a significant proportion of lower-income children being cared for by individuals other than their parents (Martin, 2015). Subsequently, these children may be considered burdensome for a household with limited available resources resulting in sub-optimal care being provided.

3.1.2. Descriptive Statistics

Table 3.1 contains the panel weighted means and standard errors for all variables employed in the primary sub-sample. These have been disaggregated between those with and those without piped water to illustrate observable differences in variables between the two cohorts[15]: The first row illustrates that nearly three quarters of the sample have access to the analysis' definition of piped water.

Table 3.1: Summary Statistics of Household and Locality Characteristics (Panel Weighted; Rural)

Variable	Sample	N	Mean	Std. Error
FULL SUB-SAMPLE				
Access to Tap	Whole	17205	0.7469	0.0315
Weekly Municipal Refuse Removal	Treated	12337	0.09	0.0166
	Control	4811	0.0157	0.0044
Cooking with Electricity	Treated	12339	0.5942	0.03
	Control	4813	0.3336	0.0445

[13] The combination of the variables measuring refuse removal and cooking energy source offer superior variation and saw the rejection of a third measure – whether street lighting is present and/or operational - due to collinearity.
[14] A quality toilet is defined as either a flush toilet with on or offsite disposal or as a chemical toilet.
[15] These are referred to as the treatment and control respectively.

Presence of Toilet	Treated	12363	0.1806	0.0162
	Control	4793	0.0709	0.0088
Real Monthly HH Income	Treated	12384	3848.64	1698169
	Control	4821	3145.37	225.9941
Real Monthly District Income	Treated	12384	4102.65	156.9664
	Control	4821	3318.92	208.2355
Real Monthly Region Income	Treated	12384	4579.18	154.6714
	Control	4821	3797.72	121.9163
Avg. HH Education of Adults	Treated	10800	8.095	0.1689
	Control	3997	6.9986	0.406
Avg. Education of Cluster	Treated	12384	6.0693	0.1053
	Control	4821	5.2858	0.1816
Avg. Education of Region	Treated	12384	6.2041	0.0972
	Control	4821	5.556	0.0776
Metro	Treated	12384	0.02	0.0133
	Control	4821	0.006	0.0047

All variables demonstrate differences between treated and control cohorts, confirmed by rejected t-tests of equivalence. Households with piped water access are more likely to have access to electricity, and are cleaner, more sanitary environments. Households with greater earnings and a greater aggregate educational attainment are more likely to have access to piped water. These earnings and educational effects hold for both regional and district levels.

Similar disparities between the two cohorts are observed for individual level variables contained in Table 3.2 below. Households with piped water access have a higher average level of educational attainment for the primary caregiver with caregivers being more likely to be the child's parent. The age of the children and the number of children cared for by each primary-caregiver is seemingly similar between the two cohorts.

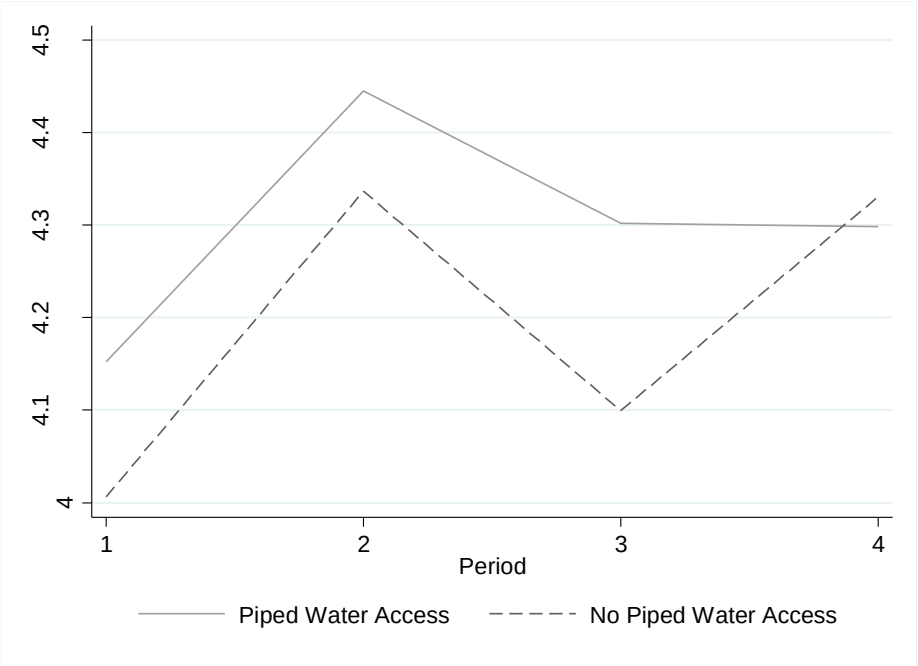
Table 3.2: Summary Statistics on Individual Characteristics (Panel Weighted)

Variable	Sample	N	Mean	Std. Deviation
FULL SUB-SAMPLE				
Perceived Child Health Status	Treated	10069	4.295	0.019
	Control	3936	4.144	0.0365
No. of Children per Caregiver	Treated	12065	2.7277	0.0681
	Control	4697	2.7908	0.0833
Primary Caregiver is Parent	Treated	11451	0.6671	0.0142
	Control	4465	0.6197	0.0183
Age (Child)	Treated	12384	8.593	0.0658
	Control	4821	8.5741	0.0848
Highest Educational Attainment of Primary Caregiver	Treated	8534	8.0096	0.2116
	Control	3076	6.9397	0.4211

Figure 3.1 below contains means of the ordinal value of perceived child health. These values are separated between the NIDS sample periods 1 to 4. The solid line reflects the health measure for those children with piped water access and the dashed line those without. With the exception of period

4, the figure illustrates that children with access to piped water have a higher mean value of health. Both cohorts furthermore follow similar trends with the exception of period 4. As a result, there exists the potential for an exogenous shock in the final period as there is a divergence in measures between the two groups with a relative deterioration in the health status of children with piped water access.

Figure 3.1: Mean Child Health by Period and Water Access



3.2. *Supplementary Data*

Exploration into the key findings of the NIDS are conducted through a pooled cross-section provided by the General Household Survey (GHS). The GHS is surveyed annually by Statistics South Africa, is nationally representative and contains individual, household and derivable regional level data. A number of variables surveyed in the GHS are equivalent in definition to that of the NIDS although the GHS has a far wider range of topics and specifics covered. The broader array of information surveyed in the GHS provides a richer dataset with which the primary conclusions can be unpacked and understood, overcoming the explanatory limitations of the NIDS data. To ensure consistency in this tier of analysis, data is pooled from years in which NIDS was sampled. Due to the absence of key variables of interest in the 2008 GHS survey, data from 2009 was used. The total GHS sample contains observations from 468 414 individuals. The GHS provides individual and household level sample probability weights, the latter being used in the estimation process insofar as a number of household level measures are employed. Standard errors were clustered at the PSU level.

3.2.1. Variable Discussion

A range of dependent and control variables were employed with the control variables being structured to replicate those used in the NIDS analysis as closely as possible. One notable deviation in definition is that of the treatment variable measuring access to a piped water source. The GHS questionnaire is broader and includes the option of identifying access type as a neighbor's tap. This is included in the GHS definition of the dummy variable in addition to the NIDS definition identified above. The neighbours tap source accounts for 2.97 % of total water source use and is thus a negligible inclusion. The expansion in the variable is theoretically valid, as the goal of the analysis is to measure the health benefits of general piped water access. It is assumed that within the NIDS survey, individuals who make use of a neighbors tap would identify the source as either a public or a private tap in the absence of the neighbor source option. Regional level variables have been aggregated at a higher level, as only a provincial identifier is available. Four key variables unique to the GHS are employed to capture the determinants of perceived water safety and measure whether an individual considers the water from their primary source to be clear, free from odor and good in taste. These observable components of water quality provide insight into the manner in which individuals evaluate the standards of their water.

3.2.2. Descriptive Statistics

Table 3.3 contains the weighted means and standard errors for all variables used in the supplementary analysis that are distinct from those of the NIDS. Variables employed in the GHS data that are equivalent to that of the NIDS are contained in Table 8.4 in the appendix. All measures are pooled across time, reflecting the manner in which they were analysed.

Table 3.3: GHS Summary Statistics of Individual Characteristics (Sample Weighted; Rural)

Variable	Sample	N	Mean	Std. Deviation
FULL SUB-SAMPLE				
Access to Tap	Whole	115837	0.704	0.0094
Water Perceived as Safe to Drink	Treated	81785	0.976	0.0020
	Control	32268	0.573	0.0144
Water is Free from Odors	Treated	81354	0.969	0.0029
	Control	32146	0.661	0.0142
Water is Clear	Treated	81748	0.966	0.0026
	Control	32219	0.627	0.0136
Water is Good in Taste	Treated	81707	0.954	0.0032
	Control	32230	0.611	0.0138
Water is Treated before Use	Treated	80925	0.059	0.0039
	Control	31805	0.187	0.0088

The above table illustrates that significant discrepancies in the perception of water quality exist between sources that are either piped or not. On average, piped water is considered superior in its

safety to consume, its odor, its clarity and its taste. Individuals with access to piped water are almost 13% less likely to treat it preceding use than those without piped water.

4. ECONOMETRIC METHODOLOGY

The strategy pursued incorporates elements of impact evaluation, seeking to robustly illustrate the direct effects of participation in a program or intervention (Mulcahy & Kollamparambil, 2016; Blomquist, 2003). The methodology makes use of a quasi-experimental sample space in addition to the full sample to establish appropriate counterfactuals for program participants by overcoming differences in (un)observable characteristics between program participants and non-participants. The quasi-experimental sample space affirms the findings of the concluding and most robust model wherein the construction of exogenous variables establishes an argument for causality in the absence of experimental data and randomisation into treatment.

A total of 4 models were estimated, each increasing in sophistication and robustness by improving in capacity to account for potential biases of the treatment estimate generated by confounding factors, endogeneity and non-random self-selection into treatment (Mulcahy & Kollamparambil, 2016). The rigour and methodology of the strategy leverages the panel structure of the data, allowing for individual-specific effects and time invariant unobservables to be controlled for. Within each model, piped water access is interacted in separate iterations with each of the minimum level of educational attainment dummies. This seeks to establish whether there exists a key level of care-giver education that is a necessary condition for guaranteeing positive child health benefits in the presence of piped water. This would be evidenced by a statistically significant result at a key level, below which all measures offer no evidence of statistical significance. Preceding the estimation with interactions, a baseline model is measured which includes a continuous care-giver educational attainment measure and its second order polynomial as explanatory variables[16]. This provides a measure of the independent impacts of care-giver education and piped water access on child health. All interactions and main effects are included, saturating the model.

4.1. Model I

The foundational model provides a naive benchmark for which the subsequent models can be compared. OLS has come to be the workhorse of empirical economics due to its simplicity in

[16] A total of 78 estimates have been evaluated when including the baseline regressions in addition to each of the 4 models' interactional regressions.

application and ease of interpretation. Within this study though, the OLS estimator is inappropriate due to the discrete and ordinal nature of the dependent variable which would induce biased estimates (Liao, 1994; Borooah, 2002).

An ordinal probit was employed which measures the impact of explanatory variables in measuring the probability of an increase in the level of the dependent variable. The ordinal probit assumes the existence of a continuous, unobservable latent variable (Y*) which determines the likelihood of observing a given level of the dependent variable (Borooah, 2002). Estimates are measured through maximum likelihood to establish the highest probability of observing a movement in the level of the dependent variable. The latent regression is summarised in vector notation as follows:

$$Child\ Health^*_{i,t,} = \beta_0 + \beta_1(PipedWater_{i,t} * CareGiverEducation_{c,i,t}) + \beta_2 PipedWater_{i,t} + \beta_3 CareGiverEducation_{c,i,t} + \beta_4 X_{i,t} + \beta_5 \eta_t + \varepsilon_{i,t}$$

Where:
(1) Subscripted i and t are individual and time identifiers respectively;
(2) Subscripted c is the level of educational attainment identifier;
(3) X is the vector of control variables;
(4) η_t are time identifiers to capture trends in child health;
(5) ε is the composite error containing both time invariant unobservables and the conditional error: $\varepsilon_{i,t} = a_i + u_{i,t}$..

The value of the dependent variable is only observable when the latent variable crosses one of a series of threshold levels in probability (Hedeker & Gibbons, 1994). The ordinal probit partitions estimations into regions based on the levels of the dependent variable. The value of the dependent variable is realised when the latent variable settles within the space of 2 neighbouring probability thresholds μ_i and μ_{i-1}. This probability is the difference between the two adjacent cumulative probabilities (Liao, 1994). In the case of this study, the continuous nature of the latent variable, *Child Health** is unobservable with the dependent variable's realisation estimated through the interval decision rule:

$$\begin{aligned}
Child\ Health &= 1 \mid X_i \text{ if } (Child\ Health^* \leq \mu_1) \\
Child\ Health &= 2 \mid X_i \text{ if } (\mu_1 \leq Child\ Health^* \leq \mu_2) \\
Child\ Health &= 3 \mid X_i \text{ if } (\mu_2 \leq Child\ Health^* \leq \mu_3) \\
Child\ Health &= 4 \mid X_i \text{ if } (\mu_3 \leq Child\ Health^* \leq \mu_4) \\
Child\ Health &= 5 \mid X_i \text{ if } (\mu_4 \leq Child\ Health^* \leq \mu_5)
\end{aligned}$$

The consistency and efficiency of the model necessitates 'parallel lines' whereby the coefficients of all explanatory variables are equal between adjacent levels of the dependent variable

(Borooah, 2002). If confirmed, the assumption is evidence that the measurable distance between each of the levels of the dependent variable are equivalent (Borooah, 2002). Subsequently, the single estimated coefficient value of a given explanatory variable is representative of the probability of increasing one level in the dependent variable regardless of what the level of the dependent variable may be. The parallel lines assumption is tested for and confirms that the coefficients for 17 of the 20 explanatory variables are equivalent across all levels at the 5% level of significance. The Brant test rejects the equivalence of *Metro, Regional Income* and *District Education.* The results of the Brant and Wald test of the assumption are contained in Table 8.5 in the Appendix. Errors are further assumed to be randomly, normally and homogeneously distributed.

The estimator is limited due to: the absence of an appropriate counterfactual which may bias results in the presence of self-selection, and; it not leveraging the panel structure of the data which establishes a likelihood that control variables and the treatment variable are correlated with time invariant unobservables captured in the composite error.

4.2. Model II

The second model employs panel data methods in conjunction with the ordinal probit estimator (Hedeker & Gibbons, 1994). Panel data estimators leverage the repeated observations on individuals to increase accuracy in estimates by controlling for both time-invariant, unobserved individual heterogeneity and time-invariant, omitted variables (Verbeek, 2012). The vector notation outlined below illustrates the existence of these individual specific, time-invariant unobservables captured within a_i. The nature of the a_i can be considered as either having fixed effects (FE) or random effects (RE). A one way RE estimator was employed which permits the existence of group specific effects and estimates separate intercepts for each individual (Wooldridge, 2002). In contrast to the FE estimator which purges the model of all time-invariant characteristics, time-invariant variables remain estimable leading to greater insights. The model assumes independently and identically distributed errors as well as the constancy in variance for individual effects (Wooldridge, 2002).

$$\begin{aligned} Child\ Health^*_{i,t,} = {} & \beta_0 + \beta_1 (PipedWater_{i,t} * CareGiverEducation_{c,i,t}) + \beta_2 PipedWater_{i,t} + \\ & \beta_3 CareGiverEducation_{c,i,t} \\ & + \beta_4 X_{i,t} + \beta_5 \eta_t + a_{i.} + u_{i,t} \end{aligned}$$

The model is limited due to the absence of appropriate counterfactuals and the requirement of meeting limiting and potentially unrealistic assumptions to ensure consistency. For efficient and unbiased estimates, the model necessitates the orthogonality of the vector $a_{i.}$ to explanatory variables

whereby there is no correlation between independent variables and individual specific, time-invariant unobservables. This is otherwise referred to as strict exogeneity and is a largely unrealistic assumption: individual specific attributes such as resilience in health and learned appropriate hygienic practices may be correlated with explanatory variables (Verbeek, 2012). As a result, the model likely suffers from biases due to unobserved heterogeneity and error autocorrelation[17] (Wooldridge, 2002).

4.3. Model III

The third model is a difference in difference (DiD) estimator. Estimates were conducted within a quasi-experimental sample space whereby outcomes between a treatment and control cohort were compared for two pre-treatment and two post-treatment periods. The shrinkage in sample size to 1452 children across all periods justifies the experimental space only be employed with the DiD. Consistent with the preceding models, an ordinal probit was employed.

Individuals in the treatment group had two initial periods without piped water access, followed by two periods with piped water access. The control group never has piped water access throughout the sample period. The first differencing occurs within each cohort and is captured by *Post*, comparing pre-treatment and post-treatment values. This differencing operates to capture changes in outcomes common to both the treated and control groups resultant of differences in the pre and post treatment trends. The second differencing occurs between the two cohorts to control for differences in permanent characteristic between the treated and control groups. This is captured by the treatment identifier, *PipedWater*. The interaction of the two is the DiD estimator, identifying a change in trend in the post-treatment period that is the result of treatment status. This variable is interacted with the vector of educational attainment variables.

$$Child\ Health_{i,t} = \beta_0 + \beta_1(PipedWater_{i,t} * Post_t * CareGiverEducation_{c,i,t}) + \beta_2 PipedWater_{i,t} + \beta_3 CareGiverEducation_{c,i,t} + \beta_4 Post_t + \beta_5 X_{i,t} + \beta_6 Z_i + \varepsilon_{i,t}$$

Where:
(1) $X_{i,t}$ contains all remaining interactions leading to a saturated model;
(2) Z_i contains all time-invariant individual specific effects;
(3) Further notation is as appeared in 4.1

Individual fixed effects were included to account for individual specific variation in health outcomes, independent of estimated controls. The process thus purges the model of the time-invariant individual specific effects that remain in Model II. This was made possible due to the decreased

[17] The estimator was elected due to the computational burden associated with estimating an ordinal probit FE within a sample with a large number of individuals.

computational burden associated with estimates in a smaller sample space that inhibited the estimation of FE in the second model. Furthermore, the FE estimator allows for the use of probability weights – of significant relevance when considering Models III-I and III-II.

The DiD estimator requires the establishment of the parallel trend assumption to ensure valid results. The assumption states that the conditional pre-treatment trends in the dependent variable should be equivalent for the treatment and control groups (White & Sabarwal, 2014). Deviation in post-treatment trends is thereafter considered a function of treatment status, leading to an unbiased estimate of the treatment effect assuming no omitted variable biases exist (White & Sabarwal, 2014). The parallel trend assumption has few widely-accepted tests beyond visual inspection. The test pursued in this study established the existence of a pre-treatment parallel trend through regression (Mora & Reggion, 2012). All control variables and individual fixed effects were employed within the pre-treatment quasi-experimental sample space with child health serving as the dependent variable. A full set of interactions between each time-period and treatment status was employed with the control group in period 1 serving as the baseline intercept. During periods 1 and 2, treatment status does not confer a statistically significant impact on the dependent variable i.e. pre-treatment dynamics do not differ between treatment and control cohorts[18] (Mora & Reggio, 2014).

The estimator suffers due to the potential for self-selection on (un)observables which leads to imbalances in characteristics between the treatment and control groups (Rosenbaum & Rubin, 1983). This necessitates measures be taken to account for potential structural differences between the two cohorts. Furthermore, unavoidable biases induced by an ordinal probit in the presence of fixed effects remains[19] (Greene, 2002). The degree of this bias is a negative function of the number of T in the data which informs group size and mimics the trajectory of the biases of the standard binary probit in terms of response to changes in T and N (Baetschmann *et. al.* 2011; Greene, 2002). Through the use of Monte Carlo simulations, Greene (2002) demonstrated that the bias observed within the ordinal probit FE model falls rapidly as T exceeds 3. On average, standard errors are calculated as being underestimated by approximately 12.7% when T=8 (Greene, 2002). Underestimated standard errors in conjunction with overestimated coefficients leads to inflated measures of statistical significance.

[18] Two estimators were employed to ensure robustness. In the first case an ordinal probit regression produces P>|z|-statistics of 1.00 and 0.152 for periods 1 and 2 respectively. In the second case, a linear regression produced t-statistics of 1.15 and -1.12 for periods 1 and 2 respectively.

[19] The biases are the result of the problem of incidental parameters. The presence of a large number of observations (each with idiosyncratic individual-specific effects) proves challenging for maximum likelihood estimation. For further elaboration, see Moon *et. al.,* (2014).

Within the current literature, investigation into how to reconcile estimators with ordinal dependent variables and fixed effects is being pursued. At present no single approach is universally considered as superior whilst the accessibility of these methods remains limited[20]. Furthermore, the necessary reduction in the number of individuals sampled to create the quasi-experimental DiD sample space has resulted in small sample concerns calling into question the power of the estimates.

4.3.1. Model III-I

The first variation of the DiD estimator makes use of propensity score matching to overcome the shortfalls of the standard DiD. The methodology draws inspiration from Galiani & Gertler (2005) although the use of an ordinal probit in contrast to OLS is a significant difference. Matching establishes appropriate counterfactuals for the treated on the basis of pre-treatment observable characteristics. To overcome the 'curse of dimensionality' induced by the use of a range of explanatory variables, a balancing score is created for each individual which reduces the vector of covariates to a single value that measures the likelihood of treatment status, whereby $0 < P(T=1|X) = P(X) < 1$. Rosenbaum (2002) demonstrated that individuals with equivalent propensity scores will have equivalent distributions in covariates, thus providing a tool to establish appropriate counterfactuals on the bases of similarities in propensity scores.

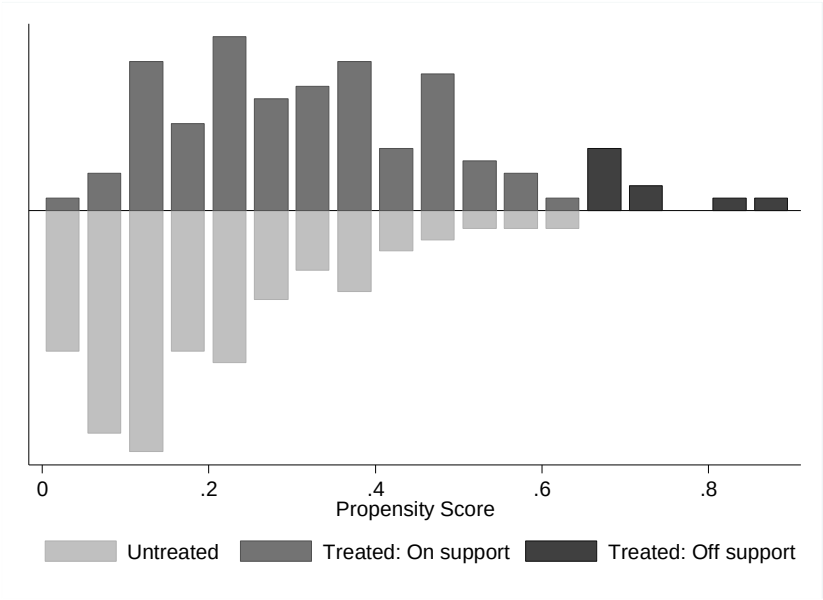
A forward-stepwise logit regression with a tolerance of 0.15 was estimated covering the most recent pre-treatment period to identify the characteristics significant in determining the likelihood of treatment status (Imbens & Rubin, 2015). The stepwise approach was led by the potential existence of non-a-priori and arbitrary differences between treated and control cohorts that may be the result of a quasi-experimental sample space[21]. The relevant characteristics that required balancing included *Age*, *Age*^{2}, *Children per Caregiver*, *Cooking with Electricity* and *Mean Regional Education*. A full output of the stepwise regression is contained in Table 8.6 in the appendix. Period 2 was elected as the source of pre-treatment data as it offers a superior vector of characteristics from which to establish a propensity score due to its proximity to the treatment period.

[20] For further insights and experimentation with newly proposed methodologies, see (Baetschmann *et. al.,* 2011)

[21] The variable pertaining to refuse removal was rejected by the stepwise due to issues of estimability whilst the variable concerned with the household existing in a metropolitan area was rejected due to collinearity. Within the quasi-experimental sample, individuals within the treatment cohort that reside within a metro account for 0.006% of the treatment group and 0% of the control. Individuals who have refuse removed at least once a week account for 10.4% of the treatment and 0.005% of the control group and. Thus, their absence is considered to be of little relevance within the quasi-experimental space.

Propensity scores were created using a logit estimator in the *psmatch2* package in Stata. In accordance with the literature, only observations within the common support were incorporated ensuring that appropriate counterfactuals remain and are studied. Subsequently observations with a propensity score below 0.01259 and above 0.63498 were excluded. Figure 4.1 below illustrates the resultant propensity score overlap.

Figure 4.1: Propensity Score Overlap



Balancing tests were conducted following estimation of the propensity score, validating the strategy as all pre-treatment characteristics fail to reject t-tests of equivalence. This is contained in Table 8.7 in the appendix, which demonstrate for the treatment and control groups the observable differences prior to and observable similarities following matching. The matching process led to a fall in mean bias due to covariate imbalances from 37.4% to 8.4%. It is argued that the methodology has correctly accounted for assignment into treatment status based on observables, ensuring that the conditional independence assumption holds (Heinrich *et. al.,* 2010). As such treatment status is 'as good as random' whereby $Y_0 \perp Pipe \mid X$ (Heinrich *et. al.,* 2010).

The difference-in-difference estimates are conducted within this refined sub-sample whereby all observations are on common support and weighted by the propensity score leading to a weighted average of the mean difference in outcomes between the matched treated and control cohorts (Caliendo & Kopeinig, 2005; Heinrich *et. al.,* 2010). The estimator would suffer endogeneity biases if

treatment status is a function unobservables. Should these unobservables be time-invariant, the DiD approach will eliminate this bias through the differencing process (Heinrich *et. al.,* 2010).

4.3.2. Model III-II

The second variation in the DiD makes use of a non-parametric kernel weighting. The methodology replicates the preceding model, first employing a stepwise logistic regression and thereafter generating a propensity score with a logit estimated on pre-treatment characteristics. Observations are trimmed to ensure overlap within propensity scores and successfully tested for balancing. A further action is taken, whereby the propensity score is employed to create a Gaussian kernel weighting with a *psmatch2* standard bandwidth of 0.06. Kernel matching makes use of weighted averages of all observations in the control to create a counterfactual and has the capacity to reduce variance (Caliendo & Kopeinig, 2005; Heinrich *et. al.,* 2010).

Weights are reflective of the quality of match, calculated as the distance between the propensity score of each treatment case and all control cases. By making use of all available data, a potential drawback is the use of observations that are possibly bad matches. Regardless, the estimator leverages the maximum possible information within the sample-space – valuable within a small sample context. The kernel weights are included as probability weights in the original specification. Table 8.8 in the appendix illustrates the success of the balancing process with the mean bias associated with covariate imbalances falling from 37.4% to 1.5%. The DiD estimator continues to suffer from potential endogeneity through correlation between covariates and time variant unobservables and/or omitted variables. Furthermore, a small number of observations in the quasi-experimental sample is an argument for low statistical power whilst bias induced by an ordinal probit in the presence of FE remains.

4.4. Model IV

The final model overcomes the biases and methodological limitation that remain in Model III. With the advent of increasingly accessible computational power, estimators that are less dependent on strong assumptions are growing in popularity and application (Roodman, 2009). The generalised method of moments (GMM) is one such estimator with a variation of it - the system GMM developed by Arellano and Bover (1995) – being employed as the final model within the user written Stata package *xtabond2*. The estimator is reflective of the fact that high quality and exogenous instruments are not always readily available and assumes that, "[t]he only available instruments are "internal" –

based on lags of the instrumented variables" (Roodman, 2009: 100). The system-GMM is an extension of the standard, semi-parametric GMM whereby moment conditions of the sample data are employed to establish estimates regardless of whether there are more moments than parameters (Zsohar, 2010). The process uses a two-step iteration whereby an objective function is minimised through establishing an optimal weighting matrix that generates consistent and efficient estimates (Ackerberg *et. al.*, 2014).

The system GMM is capable of consistent estimation with hetereogeneity of unknown form, autocorrelation, and an absence of knowledge of the nature of variable distributions (Roodman, 2009; Efendic *et, al.,* 2009; Zsohar, 2010). The panel estimator is highly appropriate for this analysis as it is adapted to function with a small number of time periods and a wide range of individuals ('small T and large N') whilst purging individual fixed effects (Roodman, 2009).

The system GMM assumes that not all covariates are exogenous and that current realizations of the variable may be a function of past realisations (Roodman, 2009). The estimator accounts for this through processes of data transformation which allows the analyst to employ all available data in some form of instrument that is (following transformation) no longer correlated with fixed effects and can be considered exogenous (Roodman, 2009). Both the original specification and the transformed specification are employed simultaneously as a system.

As suggested by Roodman (2009) all available covariates were made use of as an instrument. The system-GMM differentiates between strictly exogenous, predetermined and endogenous instruments. The nature of transformation is reflective of these definitions which determine the manner in which the variable is correlated to contemporaneous and past realizations of itself and the transformations necessary to purge correlation between observations and present and past errors. For a predetermined instrument, the contemporaneous transformation of Δ t (differencing between t_0 and t_{-1}) is considered exogenous. Thus, lags of a single period or more are employed. With regards to endogenous variables, the transformation, Δt_{-1} serves as a valid instrument (differencing between t_{-1} and t_{-2}), necessitating 2 or more lags be employed. The transformation pursued is a 'forward orthogonal deviation' which accounts for potential gaps in the panel and maximises sample size (Roodman, 2009:104). Furthermore, the estimates are conducted with the two-step command which, in conjunction with White robust standard errors outputs a limited-sample adjusted two-step covariance matrix and consistent and efficient estimates (Roodman, 2009; Efendic *et. al.,* 2009).

Post-estimation analyses are conducted through Hansen and Sargen tests of exogeneity for the vectors of exogenous and transformed instruments to ensure that the specification pursued is correct. In the absence of certainty in defining a variable as predetermined or strictly endogenous, all variables not employed as purely exogenous instruments were transformed in the methodology appropriate for endogenous variables[22]. Across all GMM specifications the argument for causality remains valid as all coefficient estimates are efficient and consistent: the GMM diagnostic tests which demonstrate exogeneity are in every case passed and are contained in the appendix in Table 8.9. As per Roodman (2008), no definitive rules with regards to the Hansen and Sargen tests exist although arguments for best practice are apparent. Within this analysis, all tests of exogeneity breach the conventional level of significance of approximately 0.25 to 0.2 as per Roodman (2008). The *xtabond2* package furthermore estimates Hansen tests of overidentification which are in all cases passed and included in Table 8.9 in the appendix.

Roodman (2009; 2008) illustrates the effects of having too many instruments relative to sample size insofar as the Hansen test can be weakened, inflating *p* values measuring exogeneity to a perfect 1.000. Although no formal outlines exist regarding appropriate instrument set size and the threshold beyond which overidentification occurs, the instrument sets employed in the study of 48 and 46 are estimated in a sample space of 6237 observations (Roodman, 2009; 2008). The ratio of instruments to observations is far superior to those deemed worrying in the Roodman (2009; 2008) literature. Limiting the instrument count was achieved in part by the implementation of a two period lag limit to the instrument sets: the minimum space required to purge endogeneity. To contribute to the robustness of results and assist in overcoming potential overidentification, GMM instrument sets were collapsed (Roodman, 2009).

In conjunction with theoretical foundations, the post-estimation diagnostics were reviewed to determine the appropriate specification. As before, the treatment variable was interacted with all variations of the educational attainment dummy. All instrument sets are therefore equivalent across specifications with the exception of the interaction variable (i.e. the educational attainment dummy varies within each specification both as a covariate and as an instrument). The dynamic nature of the estimator is a result of controlling for a lag of the dependent variable as a further covariate and instrument.

[22] The process identified all time identification dummies as well as *Age* and Age^2 as exogenous.

4.5. Limitations

Regardless of the robustness in methodology, limitations of the study remain. These are congruent to the methodological issues associated with Models II and III as those were overcome through the use of the system-GMM estimator. The remaining limitations concern the availability of key variables within the data and the use of two concurrent data-sets within the analysis.

The lack of control for an individual's HIV/AIDS status may be cause for omitted variable biases which could inflate the treatment estimate. Individuals suffering from HIV/AIDS have compromised immune systems and are more susceptible to the threats presented by water borne illnesses and contaminants (Obi *et. al.,* 2006). Therefore, the differential in health status associated with access to quality water may be substantial between those afflicted with HIV/AIDS and those who are not, leading to inflated coefficients in the treatment indicator. The potential for this is evidenced by Obi, *et. al.* (2006) who estimate that 90% of individuals infected with HIV/AIDS suffer from chronic diarrhea – a prevalent symptom of water transmitted illness. It is argued that within the DiD, these effects are partly controlled for through the FE methodology as HIV status is time invariant following contraction of the illness. The argument is imperfect as it is self-evident that a portion of the sample may have contracted HIV/AIDS during the sampling period and that the intensity of the effects of HIV/AIDS status may vary through time. The aforementioned set of concerns are corrected for in the final model which generates exogenous variables and presents an argument for causality.

The second limitation is the result of the use of an alternative dataset to unpack the core findings of the NIDS sample. Due to the fact that individuals are sampled within each dataset independently, the GHS findings illustrate averages differences in group behavioural responses to water source type that are aligned with the findings of the NIDS. This matter is partly offset by clustering of standard errors and the use of sample probability weights which ensures national representation in both datasets' estimates. Finally, small variations in a select number of variable definitions between the two datasets exist. These differences were explicitly outlined.

5. RESULTS

The following section outlines the key results of the estimation strategy explained in Section 4 with the control and dependent variables defined in Table 8.2 of the appendix. Insofar as the analysis seeks to determine a minimum level of educational attainment for the primary caregiver as a necessary

complement to piped water access, 13 specifications of each model have been estimated. The first serves as a baseline without interaction with each of the latter 12 estimated in separate iterations using a single value of the vector of educational attainment dummies interacted with the piped water variable.

The significances of all independent variables in the baseline estimate are discussed and contained in Table 5.1. All estimates of the key variable for the alternative 12 specifications, *Pipe*EducationalAttainment,* are contained in Table 5.2, with analyses following. The key finding of the analysis is the existence of a statistically significant interaction between the level of care-giver educational attainment and piped water access: Model IV illustrates that in order to ensure that piped water access improves child health, the primary care-giver must have a minimum of 7 years of formal education. These findings are confirmed by robustness checks discussed in Section 5.1. It should be noted that all ordinal probit model estimates are coefficient values and not marginal effects. The analysis serves as a benchmarking to establish the conditions under which health benefits can be observed – analysis of the intensity of these effects is beyond the scope of this paper.

Within Models I, II and IV, the key variable of interest for the baseline specification is *Pipe*. Regarding Model III, the key variable is *Treat*Post*. Models I and II are the only of the 4 to contain a statistically significant and independent positive impact of piped water access on child health. We observe a decline in the estimated value of *Pipe* between Model I and Model II, suggesting that preceding the FE transformation, there existed an upward bias in the *Pipe* variable induced by omitted variable bias associated with time invariant unobservables. As has been demonstrated, Models I and II suffer from self-selection biases that inhibit consistent and efficient estimates.

The DiD and GMM estimators eradicated the statistically significant impact of *Pipe* observed in Models I and II. This suggests that a number of confounding factors capable of biasing estimates exist within these models and that heterogeneity in the impact of piped water exists. Model IV's findings are considered the most valid as the system-GMM estimator overcomes the sets of biases previously discussed through establishing exogeneity and purging fixed effects. Model III's findings are consistent with Model IV's and demonstrate that access to piped water does not in and of itself guarantee that there are improvements in child health and suggests the potential existence of necessary complementary conditions[23].

[23] The variable *Metro* was not outputted in Model III due to estimability issues within the quasi-experimental sample space.

The baseline DiD has a highly significant measure of *Treat*. This suggests that structural differences in outcomes exist between the treated and control cohorts with the treatment group on average having superior health outcomes. This validates the PSM approach for balancing pre-treatment observable characteristics to reduce this effect. As is observed, the coefficient value and level of significance of the *Treat* variable falls in the propensity score matched models. As such, the weighting and trimming process has accounted for a degree of self-selection into treatment and corrected for a degree of bias, although a statistically significant difference between the outcomes of two groups remains. The quasi-experimental sample space limits the sample to individuals tracked from the first period. Subsequently the sample size falls with each survey period as individuals breach the 15 years of age threshold. The *Post* variable, in conjunction with *Age* and Age^2 serves to control for the effects that the aging process may have for the health outcomes of sample members associated with increased resilience and trends in these outcomes that change through time. In the baseline DiD *Age* and its second order polynomial confers statistically significant impacts suggesting that older children have superior health outcomes and that this effect falls with the level of age. When accounted for by the PSM weighting and trimming, this effect is no longer present. The insignificance of these variables demonstrate that age is of little relevance to child health within the PSM DiD estimates, and that, subsequently, the systematic attrition associated with aging does not compromise the validity of the results.

Regarding individual, household and locality level coefficients, little systematic consistency is observed with no valid results for any of these variables being observed in the system-GMM model. It is interesting to note that, with the exception of Model II, the educational attainment variable and its second order polynomial does not play any statistically significant role in *Child Health*. Moderate standard errors and small coefficients suggest a minimal impact. Regardless, we do observe the theoretically expected signs for these two variables from the more sophisticated Models III-I, III-II and IV.

With the exception of the quasi-experimental sample space and the system-GMM, cooking with electricity is seen to incur a positive impact on the dependent variable. Once again, this measure may suffer from biases as it's significance is purged in the more sophisticated models. Within the quasi-experimental sample space, the presence of weekly refuse removal is seen to incur a positive child health benefit implying that the external sanitary environment of the household is an important factor. The DiD estimates furthermore establish that the mean regional level educational attainment

depresses health effects and is arguably a result of the structure of the quasi-experimental sample and its interaction with the ordinal probit FE induced biases.

Table 5.1: Child Health Model Outputs

	Model I	Model II	Model III	Model III-I	Model III-II	Model IV
SPECIFICATION 1						
Pipe	0.195*** [0.0604]	0.059*** [0.0221]	-	-	-	0.472 [0.3677]
Treat	-	-	2.852*** [0.774]	2.083** [0.8628]	1.948** [0.862]	-
Post	-	-	-0.878 [0.6848]	-0.153 [0.4008]	0.089 [0.3873]	-
*Treat*Post*	-	-	0.702 [0.5292]	0.288 [0.4441]	0.251 [0.4985]	-
CARE-GIVER CHARACTERISTICS						
EducationalAttainment	-0.001 [0.0113]	-0.011* [0.0588]	-0.089 [0.1732]	0.031 [0.1286]	0.079 [0.1359]	0.194 [0.3677]
EducationalAttainment²	-0.0002 [0.0006]	0.001** [0.0003]	0.002 [0.008]	-0.005 [0.0078]	-0.007 [0.0078]	-0.008 [0.0073]
Parent is Caregiver	0.103** [0.05]	0.053** [0.0221]	-0.379 [0.2897]	-0.304 [0.2944]	-0.041 [0.4141]	-0.227 [0.4979]
Children per Caregiver	0.008 [0.014]	0.009* [0.0053]	0.0844 [0.0902]	0.162 [0.1465]	0.341 [0.1708]	-0.084 [0.0803]
HOUSEHOLD CHARACTERISTICS						
Municipality Removes Refuse Weekly	0.124 [0.1407]	0.033 [0.0418]	8.392*** [0.9381]	8.363*** [1.1643]	8.534*** 1.3321	0.227 [0.6947]
Cooking with Electricity	0.092* [0.048]	0.071*** [0.0208]	0.279 [0.3835]	0.229 [0.4787]	0.001 [0.6477]	-0.715 [0.4590]
Presence of Toilet	0.148* [0.0813]	0.055** [0.0274]	-0.072 [0.8316]	-1.285 [0.8631]	-1.3455 [0.9225]	0.447 [0.4650]
Mean Adult Education in HH	0.015** [0.007]	0.003 [0.004]	0.121 [0.0898]	0.091 [0.0928]	0.034 [0.0822]	-0.08 [0.7094]
Real HH Monthly Income (1000s)	0.004 [0.0041]	0.002 [0.0019]	0.023 [0.0415]	0.031 [0.0516]	0.0089 [0.0605]	0.049 [0.0387]
DISTRICT AND REGIONAL CHARACTERISTICS						
Real Monthly Regional Income (1000s)	-0.005 [0.0262]	-0.025** [0.0103]	0.444 [0.3750]	0.172 [0.3296]	0.177 [0.3055]	0.116 [0.1793]
Real Monthly District Income (1000s)	-0.168 [0.0165]	-0.016** [0.0065]	-0.378 [0.1629]	-0.349 [0.1411]	-0.334 [0.1422]	-0.015 [0.1092]
Mean Regional Education	0.005 [0.0512]	0.036* [0.0202]	-2.087** [0.7701]	-1.111** [0.6004]	-1.305** [0.6339]	0.0103 [0.3993]
Mean District Education	-0.037 [0.034]	0.0001 [0.0116]	0.795** [0.3926]	1.059*** [0.4105]	1.260*** [0.4557]	0.152 [0.2711]
Metro	-0.287 [0.198]	0.004 [0.1036]	-	-	-	-2.867 [2.0161]
YOUTH CHARACTERISTICS						
Age	-0.00003 [0.0179]	-0.008 [0.0082]	0.361** [0.1694]	0.094 [0.1421]	0.068 [0.1316]	0.016 [0.0386]
Age²	0.0001 [0.0011]	0.001 [0.0005]	-0.0056* [0.0034]	-0.003 [0.0031]	-0.006 [0.0043]	-0.0007 [0.0019]
Child Health (Lag 1 Period)	-	-	-	-	-	-0.077 [0.0636]

TIME IDENTIFIERS						
Wave 2	0.375*** [0.0808]	0.288*** [0.0288]	-	-	-	-
Wave 3	0.151** [0.0709]	0.183*** [0.0279]	-	-	-	-0.113 [0.0884]
Wave 4	0.302*** [0.0887]	0.221*** [0.0306]	-	-	-	-0.144 [0.1960]
Sample Size	9412	15628	876	824	824	6217
R2/Pseudo R2	0.0165	-	0.315	0.297	0.309	-

*Note: ***Significant at the 1% level. ** Significant at the 5% level. *Significant at the 10% level.*
All standard errors are heteroskedasticity-consistent, White standard errors and are clustered at the PSU level.
Model III-I refers to nearest neighbor PSM and III-II Kernel Density PSM.
GMM diagnostics are contained in Table 8.9 in the Appendix, confirming the exogeneity of all instrument sets.
Exogenous Instruments: Age, Age^2, time identifiers. Endogenous Instruments: All remaining covariates (lag limit of 2).
Outputs for Models I, II and III are coefficient values.

The key findings of the paper are contained in Table 5.2 below, wherein the results of all interactional effects of all models are recorded. For Model III and its extensions, $Pipe*EducationalAttainment_i$ is reflective of $Treat*Post*EducationalAttainment_{ik}$.

Table 5.2: Child Health Model Interaction Outputs

	Model I	Model II	Model III	Model III-I	Model III-II	Model IV
SPECIFICATIONS 2 - 13						
$Pipe*EducationalAttainment_1$	-0.003 [0.0938]	-0.002 [0.0522]	1.101 [0.9453]	0.878 [0.6709]	1.172* [0.7094]	1.395 [1.9623]
*Pipe*EducationalAttainment2*	-0.005 [0.094]	-0.016 [0.0514]	0.925 [0.8418]	0.894 [0.6367]	1.256* [0.6739]	1.232 [1.9100]
*Pipe*EducationalAttainment3*	0.046 [0.089]	0.027 [0.0498]	0.651 [0.8935]	0.851 [0.6508]	1.062 [0.6893]	3.254 [2.3735]
*Pipe*EducationalAttainment4*	-0.025 [0.085]	-0.006 [0.0471]	0.685 [0.8988]	0.871 [0.6471]	1.089 [0.6940]	3.374 [4.2459]
*Pipe*EducationalAttainment5*	-0.081 [0.0853]	-0.039 [0.0447]	1.834* [0.8907]	1.815* [0.9371]	1.669* [0.9651]	1.814 [1.1696]
*Pipe*EducationalAttainment6*	0.002 [0.0876]	0.006 [0.0436]	1.533 [0.957]	1.757* [0.9277]	1.538* [0.9237]	2.431 [1.8834]
*Pipe*EducationalAttainment7*	0.014 [0.0819]	0.015 [0.0425]	1.617* [0.9736]	2.027** [0.9895]	2.017** [0.9878]	2.008** [0.9456]
*Pipe*EducationalAttainment8*	0.013 [0.082]	0.035 [0.0421]	1.511 [1.0511]	1.948* [0.7585]	2.005* 1.0115]	2.281** [0.9648]
*Pipe*EducationalAttainment9*	0.065 [0.084]	0.064 [0.0425]	3.169*** [0.9906]	4.263*** [0.7120]	4.059*** [0.7386]	1.942** [0.8762]
*Pipe*EducationalAttainment10*	0.001 [0.079]	0.047 [0.0438]	2.115** [1.0487]	3.409*** [0.7537]	3.28*** [0.7917]	1.037 [0.9236]
$Pipe*EducationalAttainment_{11}$	0.003 [0.0923]	0.066 [0.0471]	2.128** [1.0412]	3.402*** [0.7498]	3.235*** [0.7875]	0.057 [0.7911]
$Pipe*EducationalAttainment_{12}$	-0.184 [0.0124]	-0.013 [0.0561]	-0.814 [1.3469]	6.436*** [0.5864]	6.319*** [0.6168]	0.497 [1.0834]

*Note: ***Significant at the 1% level. ** Significant at the 5% level. *Significant at the 10% level.*
All standard errors are heteroskedasticity-consistent, White standard errors and are clustered at the PSU level.
Model III-I refers to nearest neighbor PSM and III-II Kernel Density PSM.
GMM diagnostics are contained in Table 8.9 in the Appendix, confirming the exogeneity of all instrument sets.
Exogenous Instruments: Age, Age^2, time identifiers. Endogenous Instruments: All remaining covariates (lag limit of 2).
Outputs for Models I, II and III are coefficient values.

It is demonstrated that higher levels of education are more likely to ensure positive health benefits for children when access to piped water is provided. The models have differing initial thresholds and rates of dissipation in impacts, yet a consistency can be inferred. Models I and II provide little evidence of the existence of a necessary complementary effect.

The quasi-experimental sample space results offer a range of potential thresholds. Interpretation of these requires cognisance of the impact of fixed effects induced bias in the presence of ordinal probit estimators: the level of significance may be inflated. As such an intuitive approach to interpretation is pursued to account for these biases and reconcile the results as valid. Within all variations of Model III, tentative suggestions of significance are observed from the 5 years of educational attainment level, falling and rising between the 5% and 10% level until 9 years of educational attainment is reached. All 3 of the DiD models are consistent in suggesting a 1% level of significance at the 9 year level of education as a necessary complementary effect to piped water access. This effect dissipates in the baseline though is persistent within the PSM. Insofar as all estimates within each model are equivalent in the sample space employed and that the only source of variation between iterations exists in terms of explanatory variable specification, the rise in significance at the 9 year level can still be considered as statistically justifiable evidence of an increase in the power of the variable in impacting the dependent variable As a result of the biases of the ordinal probit fixed effects, it may be argued that those estimates at the 10% level of significance are likely insignificant, those at the 5% potentially insignificant and likely significant at the 5% level and those at the 1% level potentially significant at the 10% level and likely significant at the 5% level. It is therefore the opinion of the author that Model III illustrates a necessary complementary effect at the 9 year level[24].

The GMM outputs contained in Model IV are more conservative in range and have a justifiable effective bandwidth at lower levels of educational attainment – statistical significance is initially established at the 7 year of educational attainment level with effects dissipating at the 10 or more years of educational attainment level. As such, there exists an overlap in estimates for the DiD and GMM models at the 9 year level. The GMM estimates are deemed superior due to its capacities discussed prior. As a result, a causal relationship exists. Regardless, the DiD provides a robustness to the findings, confirming that a bandwidth does exist within the neighborhood of 9 years. The large coefficients associated with the GMM output (ranging from 1.942 to 2.281 levels) are viable as the

[24] Section 5.1. illustrates the viability of this proposition.

ordinal measure captures an individual's perceived general health status. As ailments associated with inferior water quality can be overlapping, compounding and numerous in nature, the impact on general health is arguably more substantial than those captured within a single measure. It is therefore apparent that the lower bound of the necessary threshold exists at 7 years of educational attainment.

5.1. Robustness Checks

Due to the biases induced by ordinal probit fixed effects, restructuring of the dependent variable allowed for the application of alternative, linear estimators. This confirmed the validity of the 'intuitive' Model III and robust IV results.

As is common within the social-sciences literature, the ordinal dependent variable was collapsed into dummy format measuring whether the health of the individual is considered to be at least good (Y = 1) or otherwise (Y = 0). It is assumed within the econometrics literature that standard treatment of binary dependent variables should be conducted through the use of maximum likelihood estimators such as the probit or logit. Maximum likelihood estimators are considered superior when measuring impacts on a dichotomous dependent variable as linear estimators suffer from inappropriate tests of significance and at times generate incomprehensible results falling outside of the acceptable range of 0 and 1 (Hellevik, 2007).

Hellevik (2007) has argued that this assumption bares little statistical nor practical justification. With regards to the prevalence of impossible values, the author references Rothman (1986) who maintains that the probability of observing estimates falling outside of the theoretically acceptable range of 0 and 1 is very small and is largely the result of combinations of extreme values of the independent variables. As this issue concerns the interpretation of coefficients, it is of limited relevance to this study. With reference to the impact on tests of significance Hellevik (2007) illustrates that the failure of the homoscedasticity assumption of the linear regression in the presence of a dichotomous dependent variable is of little practical importance and impacts the certainty estimates of the regression minutely. Through conducting a total of 320 tests comparing the significances of logit and OLS estimates with dummy dependent variables, Hellevik (2007) established that no systematic tendency for differences in P-values exists. Furthermore, the average difference in P values was calculated to be highly modest at 0.0002. Within a single case was there a level of significance discrepancy between the two estimators: a P-value of 0.0497 was observed for the linear estimate and

0.0505 for the logistic[25]. As such, the analysis of a dichotomous dependent variable offers a choice in methodology, reflective of the goals in application.

Table 5.3 below contains the interaction estimates of all models with the restructured dependent variable. Models I, II and III have altered the estimator to OLS which functions to minimise the mean of the squared errors, is widely understood and simple in application. Model II has employed fixed effects as opposed to random effects. The specifications of the independent variables are equivalent to those used in the original analysis.

Table 5.3: Child Health Model Interaction Outputs - Robustness Check

	Model I	Model II	Model III	Model III-I	Model III-II	Model IV
SPECIFICATIONS 2 - 13						
Piped Water Access	0.048**	0.051*	0.131	0.046	0.078	0.055
	[0.0203]	[0.0314]	[0.166]	[0.169]	[0.1491]	[0.2129]
*Pipe*EducationalAttainment$_1$*	-0.035	-0.001	0.319	0.255	0.294	0.524
	[0.037]	[0.055]	[0.285]	[0.279]	[0.2256]	[0.9338]
*Pipe*EducationalAttainment2*	-0.038	0.0004	0.293	0.267	0.312	0.467
	[0.038]	[0.059]	[0.263]	[0.273]	[0.2190]	[0.9267]
*Pipe*EducationalAttainment3*	-0.018	0.035	0.277	0.276	0.287	0.793
	[0.035]	[0.0524]	[0.261]	[0.2702]	[0.2148]	[1.1444]
*Pipe*EducationalAttainment4*	-0.042	0.007	0.286	0.279	0.291	0.941
	[0.035]	[0.05]	[0.2609]	[0.2700]	[0.2142]	[1.684]
*Pipe*EducationalAttainment5*	-0.039	-0.031	0.372	0.333	0.311	1.015
	[0.033]	[0.048]	[0.298]	[0.304]	[0.3024]	[0.7191]
*Pipe*EducationalAttainment6*	-0.017	-0.008	0.323	0.337	0.303	0.917
	[0.031]	[0.046]	[0.316]	[0.3166]	[0.3061]	[0.8009]
*Pipe*EducationalAttainment7*	-0.02	-0.012	0.327	0.339	0.323	0.808*
	[0.031]	[0.044]	[0.319]	[0.3282]	[0.3253]	[0.4310]
*Pipe*EducationalAttainment8*	-0.026	0.008	0.299	0.312	0.315	0.876*
	[0.031]	[0.045]	[0.356]	[0.3607]	[0.3413]	[0.4601]
*Pipe*EducationalAttainment9*	-0.02	0.048	0.505**	0.604**	0.561**	0.712
	[0.032]	[0.048]	[0.245]	[0.2491]	[0.2534]	[0.657]
*Pipe*EducationalAttainment10*	-0.035	-0.006	0.469**	0.621***	0.581***	0.084
	[0.029]	[0.044]	[0.185]	[0.1881]	[0.1794]	[0.4311]
*Pipe*EducationalAttainment$_{11}$*	-0.026	-0.02	0.479**	0.629***	0.586***	0.192
	[0.032]	[0.046]	[0.186]	[0.1914]	[0.1836]	[0.4550]
*Pipe*EducationalAttainment$_{12}$*	-0.075	-0.081	-0.083	0.403**	0.419**	0.383
	[0.039]	[0.048]	[0.255]	[0.2024]	[0.242]	[0.4945]

Note: ****Significant at the 1% level. ** Significant at the 5% level. *Significant at the 10% level.*
All standard errors are heteroskedasticity-consistent, White standard errors and are clustered at the PSU level.
Model III-I refers to nearest neighbor PSM and III-II Kernel Density PSM.
GMM diagnostics are contained in Table 8.9 in the Appendix, confirming the exogeneity of all instrument sets.
Exogenous Instruments: Age, Age^2, time identifiers. Endogenous Instruments: All remaining covariates (lag limit of 2).
Outputs for Models I, II and III are coefficient values.

[25] In summary of the findings, Hellevik (2007: 62) states: "When we look at the P-values from the linear and logistic significance tests, they were in 20% of the 320 cases completely identical with four digit probabilities. In 43% of the comparisons the difference was less than 0.001, in 90% less than 0.005".

It is observed that the minimum levels of educational attainment required to guarantee child health benefits are in accordance with the intuitive and robust levels of significance of the core model i.e. 9 years within the DiD and 7 years within the GMM. All estimates are within the theoretical bounds of 0 and 1 with no evidence of an independent impact of piped water access on child health observed in Models III and IV. This serves to confirm that the threshold years of education identified in the models making use of an ordinal dependent variable are robust to variation in specification across all models, regardless of whether fixed effects induced ordinal probit biases are present or removed.

5.2. Discussion

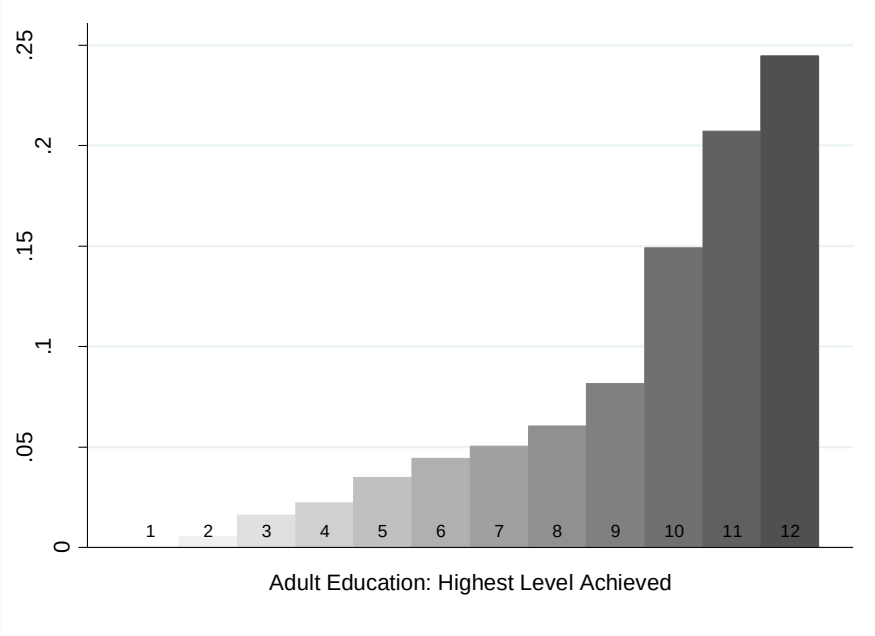
Key to understanding the enabling role of care-giver education for child health in the presence of piped water is the establishment of behavioural responses of individuals to water source type and estimating whether there exist positive biases in perceived water quality towards piped water sources. By stratifying the GHS data into cohorts of individuals based on the vector of minimum educational attainment, it is possible to measure the conditions under which water is considered safe and how the water is subsequently treated and handled by people that differ in educational history. It is assumed that the same treatment of water pursued by an adult would be provided to the child under their care.

Figure 5.1 contains the mean percentage of individuals likely to treat water that is perceived of as unsafe, grouped by level of minimum educational attainment as defined by the vector of educational attainment dummies[26]. The values have been normalised to individuals with a single year of educational attainment and rebased for this cohort to have a value of 0 to demonstrate relative differences between groups. All figures are panel weighted and clustered.

It is apparent that more educated people are more likely to treat unsafe water with a rapid acceleration in this likelihood occurring at 9 and above years of education. As per the preceding assumption, children consume the same water as their primary care-giver. Thus, children of primary care-givers who have at least 9 years of education are more likely to consume treated water that was considered unsafe preceding treatment. These results are observational and do not account for the fact that higher educated individuals may have greater resources and capacity to employ in treatment and are thus more likely to treat water due to the decreased opportunity cost of treatment.

[26] Figures regarding the treatment of water perceived of as safe have been omitted due to little variation on the basis of educational attainment i.e. a range of 0.062 to 0.066 between the first and final cohort. It may be concluded that the treatment response to water considered as safe does not vary with educational attainment.

Figure 5.1: Treatment of Water Perceived of as Unsafe by Educational Attainment Cohort



A probit regression making use of a dummy, *Treatment-of-Water,* as the dependent variable and a full vector of controls equivalent to the NIDS specifications (with the addition of the dummy *Pipe)* are employed to expand on the analysis in a more robust manner[27]. The regression on the full GHS sample establishes the statistically significant finding that individuals who consider their water to be safe are unlikely to treat piped sources. The capacity for an individual to accurately establish the safety of water is therefore a potential mechanism in the determination of treatment.

By cohorting the analysis based on educational attainment, group variations in behavioural responses to water were measured. A second probit regression was structured using the same covariates as the core analysis with *Treatment-of- Water* once again being used as the dependent variable. Additional covariates include the dummies *Pipe* and *Safe-to-Drink,* the latter measuring whether the water is considered by the individual as safe to drink or not. A total of 12 specifications were employed, each equivalent in the structure of variables but estimated on separate sample spaces. These sample spaces are limited to include individuals breaching the ranges of education defined by the vector of minimum levels of educational attainment dummies.

As illustrated in Table 5.4 below, for all cohorts both *Pipe* and *Safe-to-Drink* have a negative, statistically significant influence on the likelihood of treatment at the 1% level – individuals are less

[27] In the following analyses, the coefficients have been transformed to reflect marginal effects. As such, they represent the probability that a coefficient will affect the outcome of the binary dependent variable.

likely to treat water perceived of as safe and less likely to treat piped water when controlling for safety. The coefficient values on the perceived safety variable are in all cases larger than that of pipe (and the largest of all covariates) confirming that perceptions of water safety are the core determinant of treatment regardless of educational attainment. Furthermore, the coefficient associated with perceived safety increases in size as educational attainment increases. In contrast (and most importantly), the *Pipe* coefficients fall in size. In the determination of treatment, more educated individuals place greater weight on perceptions of water safety and less weight on source type i.e. higher levels of education increase the likelihood that an individual responds to perceptions of water safety through treatment and decreases the likelihood that they forego treating water on the basis of source type.

Table 5.4: Determinants of Treatment

	Safe-to-Drink			*Pipe*		
Cohort	Coeff.	Std. Err.	z	Coeff.	Std. Err.	z
FULL GHS SAMPLE						
Highest Attainment: 1 Year	-0.138	0.0093	-14.83	-0.042	0.0075	-5.60
Highest Attainment: 2 Years	-0.137	0.0093	-14.77	-0.042	0.0075	-5.67
Highest Attainment: 3 Years	-0.138	0.0092	-14.86	-0.043	0.0075	-5.64
Highest Attainment: 4 Years	-0.139	0.0093	-14.88	-0.041	0.0075	-5.53
Highest Attainment: 5 Years	-0.139	0.0094	-14.72	-0.041	0.0076	-5.40
Highest Attainment: 6 Years	-0.139	0.0095	-14.54	-0.041	0.0077	-5.39
Highest Attainment: 7 Years	-0.139	0.0095	-14.56	-0.043	0.0078	-5.49
Highest Attainment: 8 Years	-0.141	0.0098	-14.43	-0.042	0.0081	-5.27
Highest Attainment: 9 Years	-0.143	0.0102	-14.17	-0.042	0.0084	-5.03
Highest Attainment: 10 Years	-0.152	0.0105	-14.43	-0.038	0.0880	-4.41
Highest Attainment: 11 Years	-0.159	0.0109	-14.60	-0.034	0.0095	-3.67
Highest Attainment: 12 Years	-0.164	0.0127	-12.83	-0.033	0.0113	-3.00

Note: *All Significant at the 1% level.*
Coefficient values are marginal effects and interpretable as probabilities

In order to establish a firm understanding of the likelihood of treatment it is therefore necessary to understand the determinants of perceived water safety as this has the greatest weight in the determination of treatment likelihood. A final system of probit regressions was employed to estimate these relationships. The GHS contains information on the observable characteristics of the water a person consumes and includes data regarding whether the source is free from odor, is of an acceptable taste or is visibly clear. These, in addition to a full specification of covariates and the *Pipe* variable were employed to measure the relative weights groups of individuals place on these factors in their determination of water quality. The foundational regression on the full sample without cohorting by level of education confirms that *Clarity*, *Odor*, *Taste* and *Pipe* are highly statistically significant and

serve to inform an individual's perception of water quality[28]. The analysis is hereafter cohorted by educational attainment to establish whether variations in these weights exist between groups.

Table 5.5: Determinants of Perceived Water Safety

Cohort	*Clear* Coeff.	*Clear* Std. Err.	*Clear* z	*Taste* Coeff.	*Taste* Std. Err.	*Taste* z	*Odor* Coeff.	*Odor* Std. Err.	*Odor* z	*Pipe* Coeff.	*Pipe* Std. Err.	*Pipe* z
FULL GHS SAMPLE												
Baseline	0.094	0.0043	21.62	0.063	0.0048	13.00	0.039	0.0045	8.64	0.066	0.0043	15.33
Highest Attainment: 1 Year	0.093	0.044	21.02	0.064	0.0049	12.85	0.038	0.0046	8.29	0.065	0.0043	15.12
Highest Attainment: 2 Years	0.092	0.0044	20.94	0.064	0.0049	12.87	0.038	0.0046	8.30	0.064	0.0042	15.09
Highest Attainment: 3 Years	0.097	0.0044	20.88	0.063	0.0049	12.77	0.038	0.0046	8.22	0.064	0.0042	14.97
Highest Attainment: 4 Years	0.092	0.0044	20.87	0.063	0.0050	12.70	0.038	0.0046	8.22	0.063	0.0042	15.09
Highest Attainment: 5 Years	0.091	0.0044	20.67	0.063	0.0049	12.70	0.037	0.0046	8.05	0.063	0.0042	15.02
Highest Attainment: 6 Years	0.091	0.0044	20.49	0.062	0.0049	12.57	0.038	0.0046	8.16	0.062	0.0041	14.91
Highest Attainment: 7 Years	0.090	0.0044	20.16	0.062	0.0049	12.59	0.036	0.0046	7.71	0.061	0.0041	14.63
Highest Attainment: 8 Years	0.088	0.0045	19.56	0.061	0.0048	12.42	0.036	0.0046	7.76	0.058	0.0041	14.21
Highest Attainment: 9 Years	0.086	0.0045	18.93	0.057	0.0040	12.20	0.035	0.0047	7.58	0.053	0.0041	13.18
Highest Attainment: 10 Years	0.081	0.0045	17.89	0.057	0.0048	11.89	0.034	0.0048	7.26	0.047	0.0038	12.43
Highest Attainment: 11 Years	0.076	0.0046	16.45	0.052	0.0050	10.46	0.036	0.0050	7.32	0.042	0.0039	10.85
Highest Attainment: 12 Years	0.071	0.0052	13.65	0.053	0.0058	9.15	0.034	0.0055	6.17	0.037	0.0042	8.68

Note: Baseline refers to the complete sample containing additional covariates Adult Educated and Adult Educated²
Coefficient values are marginal effects and interpretable as probabilities

Table 5.5 above contains the marginal effects transformed covariate estimates of the fully specified probit regressions cohorted by level of educational attainment. It is observed that the observable characteristics and the source type are statistically significant determinants of perceived water safety and that the size of the coefficients of each of these variables falls as educational attainment increases.

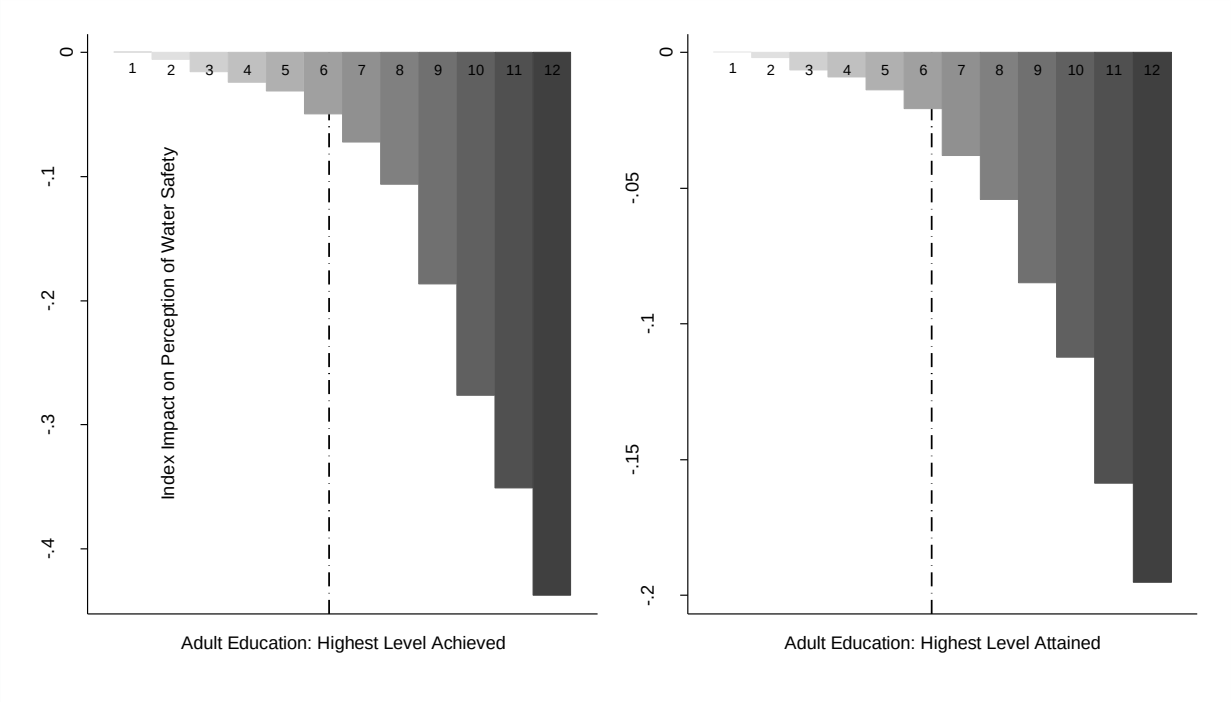
Figure 5.2 below assists in interpreting the relevance of these results. Both panels have been normalised to the first year of educational attainment and rebased to have this cohort at 0. The left panel illustrates that whilst controlling for all available factors, the relative weight placed on *Pipe* in determining the perceived safety of water falls as educational attainment rises i.e. when controlling for individual, household and contextual variables, more educated people are less likely to consider their primary water source as safe solely due to the fact that it is a piped source. The right panel contains the sums of each of the values of the observable characteristics (clarity, odor and taste) to create a simple index[29]. As illustrated, the relative weight placed on the index of observable characteristics of

[28] The baseline regression on the full sample space illustrates that *Clarity, Odor, Taste* and *Pipe* have z statistics of 22.68, 13.09, 19.95 and 1.16 respectively. This, in conjunction with respective coefficients of 1.62, 1.11, 0.68 and 1.16 suggest that the clarity of the water has the greatest weight in the determinant of water safety, with source second, odor third and taste last.

[29] Figures 7.1, 7.2 and 7.3 of the appendix illustrate the relative significance of each of the observable components.

water in the determination of perceived water safety has a negative relationship with the individual's level of educational attainment i.e. more educated people are less likely to regard water as safe when they consider it to be of observably lower quality. Interpretation of the right panel is made easier when recalling the definitions of the dummy variables included in the index. All three dummies measure superior water quality based on observables, with the highest quality of the water being considered a value of 1 in the index. As a result, individuals with a higher educational attainment are less likely to consider water that is unclear, poor in odor and poor in taste as safe. Phrased alternatively, individuals with a higher educational attainment are more likely to consider water that is free from odor, clear and good in taste as safe[30]. These factors inform the likelihood of treatment as established previously.

Figure 5.2: Weight of Determinants of Perceived Water Quality



To confirm a potential threshold difference in the trajectories of the water safety determinants' weights, the *nl hockey* package was used. Written by Mark Lunt of the University of Manchester, a linear piecewise regression allows for the establishment of an optimal knot in a bivariate relationship demonstrating where statistically significant changes in the slopes of the relationship exist. The data

[30] This is both self-evident and tested. Should the dummy variable be restructured to swap the outcomes that 1 and 0 identify, the coefficient is equivalent but with the opposite sign. For example, the coefficient for the current variable *Clear* (whereby clear water is identified as a 1) is equivalent but with opposite sign to the variable *Unclear* (whereby clear water is identified as a 0).

used to generate the preceding tables contain a significant change in slope at 6.744 years of educational attainment for the right panel and 6.875 years for the left, both indicated by the dashed lines[31]. By rounding to the nearest integer, at the 7 year of education level the rate at which the relative weights granted to piped water and observable characteristics in the determination of water safety have a structural change in trajectory. This is consistent with the lowest threshold established by Model IV and with the findings of Waddington *et. al.* (2009) – point of use treatment is a superior and the most cost effective mechanism for guaranteeing improvements in water quality and, in this context, serves to ensure that piped water is beneficial to child consumers.

The cohorted regressions demonstrates that there exists a bias towards piped water and that lower levels of education lead to a greater likelihood that piped water is assumed to be safe regardless of the observable characteristics of the water. This reduces the likelihood that the water is treated and serves as the mechanism through which education impacts child health when interacted with water source type. It is acknowledged that an individual, based on past positive experiences, may have justification in the static assumption that piped water is in fact superior in safety. Thus, there is a value of positive benefit associated with it regardless of its current state, explaining its existence as a significant determinant outside of the realm of a potential bias. This reasoning does not explain why variation in this value might exist between groups of individuals with different levels of educational attainment when controlling for household, district and regional level characteristics. As such, the finding is deemed an educationally determined bias which is reflected in the decreased weight granted to more relevant observable characteristics of the water whilst controlling for context related variables.

In summary, the analysis draws the following findings.

1) Care-givers with at least 7 years of educational attainment ensure that the health of children under their care improves in the presence of piped water.
2) The higher educated an individual, the more likely the individual treat water they consider to be unsafe for consumption. By assumption, this same water is consumed by the child under their care.
3) Educational attainment impacts the capacity for an individual to evaluate the safety of water. Higher educated people are more likely to place greater weight on observable characteristics and less likely to assume piped water as safe regardless of these observable characteristics.

[31] T-statistics are 27.65 for *Pipe* and 23.90 for *Index*.

Specifically, individuals with 7 or more years of education are better equipped to accurately assess water quality based on observables and, in accordance with point 2, respond by treating the water. This explains the findings outlined in point 1 as potential contaminants are eliminated through treatment.

The findings offer justification for some valuable and simple policy prescriptions to maximise the positive health benefits associated with piped water access. Geography specific averages of educational attainment are heterogenous by nature and readily available within the GHS and other publicly available survey data. As established by Waddington (2009: 16), intervention interacts with context and behavioural mechanisms and can influence the likelihood of adequate caution be taken to water preceding consumption. It is therefore apparent that in conjunction with the provision of piped water, programs that communicate the necessity of treatment should be provided, the intensity of which is relative to the gap between the area's mean educational attainment and the necessary threshold of 7 years.

6. CONCLUSION

Access to clean and safe drinking water contributes to an individual's wellbeing and is of particular significance to vulnerable groups who have a decreased natural immunity to contaminants. These vulnerable cohorts suffer disproportionately in the presence of unsafe drinking water as they are generally of a lower income status and have less capacity to invest in health promoting behaviours and activites. Subsequently the provision of clean, publicly provided piped water offers both social and economic gains as a healthier workforce is present, less diversions of public resources to health care are required and the time and cost pressures for households to actively ensure that water is clean preceding consumption is reduced. Unfortunately, it is not necessarily possible to guarantee that public water services are at all times fit for use at point of distribution in part due to limits in the quality of public-sector treatment, a deterioration in water quality between public source and private use and inadequate pre-consumption treatment or storage by consumers. Empirical analyses into the effects of piped water access on child health have drawn a wide range of results, illustrating that between country heterogeneity in piped water quality is present. Nonetheless, a general consensus is observed within the literature: positive health gains for children are enjoyed when improved water access type is provided. This is a function of the decreased likelihood and presence of contaminants and water borne diseases and ailments. A wide range of estimators have been employed in the literature with those most robust controlling for individual fixed effects and the biases associated with self-selection

into treatment that leads to structural imbalances in characteristics between the treatment and control groups.

Within both the South African and general developmental context, the educational attainment of the primary care-giver offers a potential complementary affect to access to technologically superior water source types as it informs an individual's behavioural response to water. Within South Africa this complementary effect is a necessary condition for ensuring that children benefit from piped water access. Through the use of both cross-sectional and panel data, the preceding analysis illustrates that there is a positive and causal relationship between child health and piped water access for individuals below the age of 15 in rural South Africa. This effect is conditional on the primary caregiver having at least 7 years of formal education. It is demonstrated that the level of an individual's educational attainment determines the degree of positive bias an individual has towards piped water, impacting the individual's capacity to accurately evaluate the quality of water. This subsequently determines the likelihood of water treatment preceding use which has a direct effect on child consumers under the assumption that both the care-giver and the child consume the same water.

The robustness of the result is ensured as exogenous variables estimated through system-GMM provide consistent and efficient estimates that do not suffer from confounding factors. South African public policy regarding water and sanitation programs geared towards the improvement of child and general health should be cognisant that individual circumstances inform program effectiveness and that these circumstances have a substantial impact on the wellbeing of children. Consequentially, sufficient effort should be invested in ensuring that adequate educational programs communicating the appropriate and safe use of water are provided in conjunction with piped water access to guarantee that positive benefits are observed.

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8. APPENDIX

Table 8.1: Summary Statistics on Household and Locality Characteristics (Panel Weighted; Rural)

Variable	Sample	N	Mean	Std. Error
QUASI-EXPERIMENTAL SAMPLE				
Access to Tap	Whole	1703	0.070	0.022
Weekly Municipal Refuse Removal	Treated	135	0.010	0.007
	Control	1562	0.007	0.004
Cooking with Electricity	Treated	135	0.431	0.137
	Control	1566	0.252	0.071
Presence of Toilet	Treated	134	0.079	0.033
	Control	1561	0.046	0.012
Real Monthly Household Income	Treated	135	2660.33	298.947
	Control	1568	3011.8	277.445
Real Monthly District Income	Treated	135	3253.35	161.326
	Control	1568	3155.71	364.179
Real Monthly Region Income	Treated	135	4169.27	197.603
	Control	1568	3506.24	127.571
Average Household Education (Adults)	Treated	111	7.077	0.288
	Control	1339	6.380	0.800
Average Education of Cluster	Treated	135	5.569	0.102
	Control	1568	4.954	0.341
Average. Education of Region	Treated	135	5.876	0.104
	Control	1568	5.309	0.073
Metro	Treated	135	NA	NA
	Control	1568	NA	NA
Perceived Child Health Status	Treated	79	4.280	0.109
	Control	1274	4.150	0.048
Number of Children per Care-Giver	Treated	135	2.090	0.222
	Control	1568	2.900	0.100
Primary Caregiver is Parent	Treated	119	0.612	0.054
	Control	1457	0.626	0.032
Age (Child)	Treated	135	11.300	0.255
	Control	1568	0.870	0.085
Highest Educational Attainment of Primary Caregiver	Treated	88	5.770	0.579
	Control	1046	6.410	0.859

Table 8.2: Description of Explanatory Variables

Variable	Source	Description	Type
Access-to-tap	NIDS; GHS	Identification of the household's main source of water X=1 if the water is sourced from: 1) Piped tap in dwelling; 2) Piped tap water on site or in yard; 3) Public Tap X=0 if otherwise	Dummy
Ref-Rem	NIDS; GHS	Identification of the frequency of removal of household refuse by municipal authorities X=1 if refuse is removed at least once a week by local authorities or peoples hired by local authorities X=0 if otherwise	Dummy
Cook-Elec	NIDS	Identification of the main source of energy for cooking X=1 if the primary source of energy is electricity from mains or a generator X-0 if otherwise	Dummy
Toilet	NIDS; GHS	Measure of the type of toilet facility used in the household X=1 if the toilet type is: 1) Flush toilet with onsite disposal; 2) Flush toilet with offsite disposal; 3) Chemical toilet X=0 if otherwise	Dummy
RHHIncome	NIDS; GHS	Real monthly household income in thousands. Deflated with world bank consumer price index data. In Rands	Continuous
RDIncome	NIDS; GHS	Real monthly district income in thousands. Deflated with world bank consumer price index data. In Rands	Continuous
RRIncome	NIDS; GHS	Real monthly regional income in thousands. Deflated with world bank consumer price index data. In Rands	Continuous
HHEduc	NIDS; GHS	Average educational attainment of adults in household. In years	Continuous
DistrictEduc	NIDS; GHS	Average educational attainment of adults in district. In years	Continuous
RegionEduc	NIDS; GHS	Average educational attainment of adults in region. In years	Continuous
Metro	NIDS	Identifier of whether household is in a metropolitan area X=1 if the household is in a metropolitan area X=0 if otherwise	Dummy
ChildPerCare	NIDS	Measure of the number of children under the care of the primary care-giver.	Discrete
CareParent	NIDS	Identifier of whether the primary care-giver is the child's parent. X=1 if the primary care-giver is the child's parent X=0 if otherwise	Dummy
Age (Child)	NIDS	Measure of the age of the child. In years.	Discrete
Educational Attainment	NIDS; GHS	Measure of the highest level of formal educational attainment of the primary caregiver. In years.	Discrete
SafeDrink	GHS	Identifier of whether the water from the primary source is considered safe to drink preceding treatment. X=1 if water is considered safe to drink preceding treatment. X=0 if water is not considered safe to drink preceding treatment.	Dummy
Odor	GHS	Identifier of whether the water from the primary source is considered free from bad smells preceding treatment. X=1 if water is free from bad smells preceding treatment. X=0 if water is not free from bad smells preceding treatment.	Dummy
Clear	GHS	Identifier of whether the water from the primary source is considered clear (has no colour/free of mud) preceding treatment. X=1 if water is clear preceding treatment. X=0 if water is not clear preceding treatment.	Dummy
Taste	GHS	Identifier of whether the water from the primary source is considered good in taste preceding treatment. X=1 if water is good in taste preceding treatment X=0 if water is not good in taste preceding treatment	Dummy

Table 8.3: Summary Statistics on Care-Giver Education Strata (Sample Weighted; Rural)

Variable	Sample	N	Mean	Std. Deviation
FULL SAMPLE				
Highest Attainment: 1 Year	Treated	8536	0.841	0.013
	Control	3076	0.798	0.028
Highest Attainment: 2 Years	Treated	8536	0.838	0.013
	Control	3076	0.786	0.028
Highest Attainment: 3 Years	Treated	8536	0.825	0.013
	Control	3076	0.762	0.029
Highest Attainment: 4 Years	Treated	8536	0.786	0.016
	Control	3076	0.720	0.030
Highest Attainment: 5 Years	Treated	8536	0.745	0.017
	Control	3076	0.655	0.034
Highest Attainment: 6 Years	Treated	8536	0.712	0.018
	Control	3076	0.609	0.034
Highest Attainment: 7 Years	Treated	8536	0.656	0.018
	Control	3076	0.544	0.038
Highest Attainment: 8 Years	Treated	8536	0.571	0.021
	Control	3076	0.478	0.04
Highest Attainment: 9 Years	Treated	8536	0.504	0.022
	Control	3076	0.407	0.042
Highest Attainment: 10 Years	Treated	8536	0.415	0.018
	Control	3076	0.346	0.037
Highest Attainment: 11 Years	Treated	8536	0.332	0.017
	Control	3076	0.268	0.028
Highest Attainment: 12 Years	Treated	8536	0.210	0.015
	Control	3076	0.171	0.024

Table 8.4: GHS Summary Statistics on Household, District and Regional Characteristics (Panel Weighted; Rural)

Variable	Sample	N	Mean	Std. Error
FULL SAMPLE				
Weekly Municipal Refuse Removal	Treated	82984	0.071	0.0067
	Control	32853	0.015	0.0028
Cooking with Electricity	Treated	82984	0.571	0.0095
	Control	32853	0.364	0.0134
Presence of Toilet	Treated	82848	0.116	0.0078
	Control	32808	0.064	0.0059
Real Monthly Household Income	Treated	82984	136355	10330.06
	Control	32853	99174.9	11517.13
Real Monthly District Income	Treated	82984	132857	9680.7
	Control	32853	3318.92	208.2355
Real Monthly Region Income	Treated	82984	218824	4586.676
	Control	32853	224463	6284.86
Average Household Education (Adults)	Treated	51731	8.704	0.0559
	Control	19524	8.111	0.0769
Average Education of District	Treated	82984	6.227	0.0433
	Control	32853	5.587	0.0555
Average. Education of Region	Treated	82984	7.057	0.0176
	Control	32853	7.041	0.0197

Note: Metro variable alternatively defined in GHS and excluded

Table 8.5: Parallel Lines Assumption Testing Results: 0.05 Level of Significance

Variable	P-Value
QUASI-EXPERIMENTAL SAMPLE	
Access to Tap	0.257
Weekly Municipal Refuse Removal	0.902
Cooking with Electricity	0.943
Presence of Toilet	0.692
Real Monthyl HH Income	0.544
Real Monthly District Income	0.901
Real Monthly Region Income	0.023
Avg. HH Education of Adults	0.274
Avg. Education of Cluster	0.008
Avg. Education of Region	0.939
Metro	0.001
No. of Children per Caregiver	0.758
Primary Caregiver is Parent	0.317
Age (Child)	0.197
Age2 (Child)	0.747
Care-Giver Education	0.369
Care-Giver Education2	0.334
Period 2	0.214
Period 3	0.277
Period 4	0.238
Wald Test Prob > Chi2	0.172

Table 8.6: Forward Stepwise Logit Outputs

Variable	Coefficient	Std. Error	z	P>|z|
QUASI-EXPERIMENTAL SAMPLE: PRE-TREATMENT				
Age	0.742	0.253	2.93	0.003
Age^2	-0.0401	0.0157	-2.55	0.011
Children Per Care-Giver	-0.253	0.156	-1.62	0.105
Mean Regional Education	1.807	0.806	2.24	0.025
Cook with Electricity	-0.894	0.618	-1.45	0.148
Sample Size	293			
Pseudo R^2	0.1627			

Table 8.7: PS-Matching T-Test Results - Logit

Variable	Sample	Mean Treated	Control	% Bias	|%| Bias Reduction	t-test t	p>|t|
QUASI-EXPERIMENTAL SAMPLE							
Age	Unmatched	9.1386	8.1124	29.9		2.55	0.011
	Matched	9.1087	8.5978	14.9	50.2	1.02	0.309
Age²	Unmatched	93.673	79.03	25.1		3.72	0.00
	Matched	93.457	86.228	12.4	50.6	2.18	0.03
Children Per Care-Giver	Unmatched	2.2277	3.1124	-62.7		-5.38	0.00
	Matched	2.2826	2.2935	-0.8	98.8	-0.06	0.955
Cook with Electricity	Unmatched	0.15842	0.2426	-21.1		-1.79	0.075
	Matched	0.16304	0.13043	8.2	61.3	0.62	0.535
Mean Regional Education	Unmatched	5.5983	5.3545	48		4.65	0.00
	Matched	5.493	5.5232	-5.9	87.6	-0.46	0.643
Mean Bias	Unmatched	37.4					
	Matched	8.4					

Table 8.8: PS-Matching T-Test Results – Kernel

Variable	Sample	Mean Treated	Mean Control	% Bias	|%| Bias Reduction	t-test t	t-test p>|t|
QUASI-EXPERIMENTAL SAMPLE							
Age	Unmatched	9.1386	8.1124	29.9		2.55	0.01
	Matched	9.1087	9.1193	-0.3	99	-0.02	0.98
Age²	Unmatched	93.673	79.03	25.1		2.18	0.03
	Matched	93.457	93.983	-0.9	96.4	-0.06	0.95
Children Per Care-Giver	Unmatched	2.2277	3.1124	-62.7		-5.38	0.00
	Matched	2.2826	2.3222	-2.8	95.5	-0.21	0.836
Cook with Electricity	Unmatched	0.1572	0.2426	-21.1		-1.79	0.075
	Matched	0.16304	0.15243	2.7	87.4	0.20	0.845
Mean Regional Education	Unmatched	5.5983	5.3545	48		4.65	0.00
	Matched	5.493	5.4888	0.8	98.3	0.06	0.949
Mean Bias	Unmatched	37.4					
	Matched	1.5					

Table 8.9: System-GMM Diagnostics

Measure	Specification											
	1	2	3	4	5	6	7	8	9	10	11	12
No. of Instruments	48	46	46	46	46	46	46	46	46	46	46	46
a) Hansen J-Test of Overidentifying Restrictions	0.767	0.538	0.567	0.656	0.848	0.887	0.767	0.881	0.760	0.586	0.430	0.544
Difference-in-Hansen tests of exogeneity of GMM instrument subsets:												
b) GMM Instrument Hansen Test Excluding Group	0.819	0.661	0.651	0.662	0.801	0.825	0.724	0.880	0.763	0.712	0.610	0.405
c) GMM Instrument Difference	0.550	0.381	0.423	0.526	0.701	0.756	0.634	0.689	0.590	0.401	0.296	0.589
d) IV Instument Set Hansen Test Excluding Group	0.555	0.747	0.739	0.807	0.937	0.910	0.881	0.958	0.895	0.739	0.345	0.420
e) IV Instrument Set Difference	0.966	0.147	0.183	0.206	0.258	0.458	0.245	0.257	0.207	0.204	0.598	0.706

Note: a) H0: Model Specification is correct with valid overidentifying restrictions
b) H0: GMM Differenced Instrument are exogenous
c) H0: System-GMM Instruments are exogenous
d) H0: GMM Instruments exluding IV set are exogenous
e) H0: IV Instument set is exogenous
See Efendic *et. al.*(2009)

Figure 8.1: Relative Coefficient Weight in Determining Water Safety: Clarity of Water

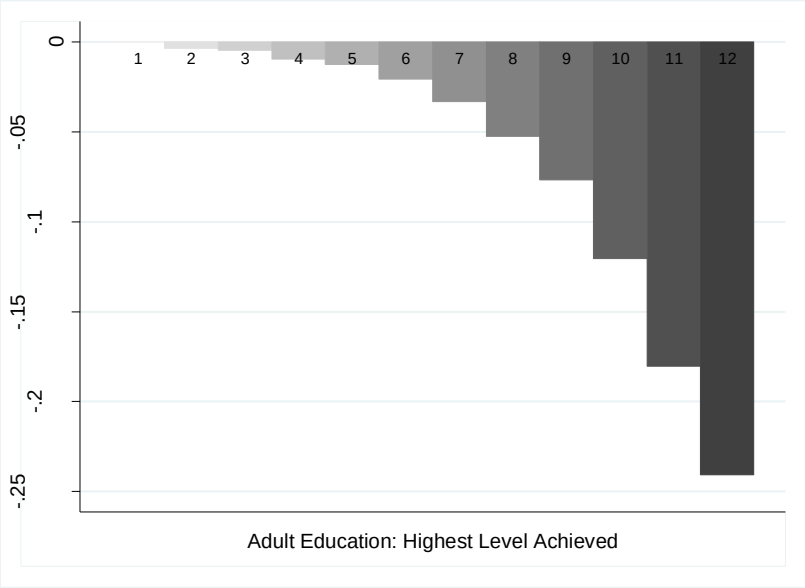


Figure 8.2: Relative Coefficient Weight in Determining Water Safety: Odor of Water

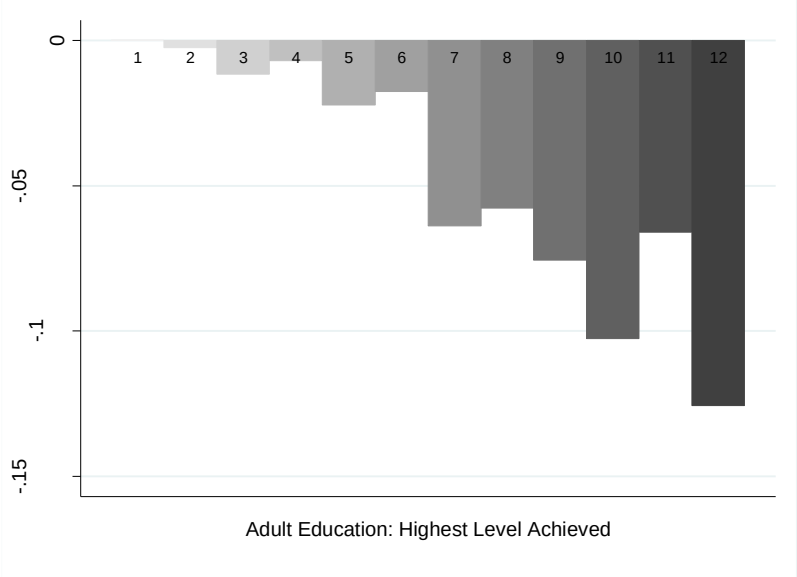


Figure 8.3: Relative Coefficient Weight in Determining Water Safety: Taste of Water

