Household Poverty Determinants in Kenya: A Demographic and Health Survey Wealth Index Approach

by

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Abstract

This paper shows that the Demographic and Health Survey Wealth Index need to be used with caution in the analysis of household poverty in Kenya. Thus, we depict a case of varied results when the wealth index is directly used with regional comparison, and discover that in both the binary and ordered logistic models, the years of education of household head, their marital status, the size of a given household and the region of residence (province) strongly determine household welfare status. We also observe that these characteristics are even more important in explaining household probability to poorest, and thus, lay emphasis on results obtained while controlling for household region of residence (province) to those that distinguish between rural and urban households.

Introduction

Poverty is unjust. The World Bank estimates that roughly 46% of Kenyans are poor at national poverty lines. Analysis of poverty in Kenya has largely depended on traditional measures such as household incomes, expenditures and consumption levels. However, these choices of measurement variables are inherently inaccurate in a developing country setup as opposed to the case in a developed one. Data on accurate incomes, expenditures or levels of consumption are difficult to collect. The use of indices is highly instrumental in this setup where households are ranked by scores on common variables capturing their asset endowments (Miriam et al., 2004). The calculated wealth index in the DHS is such one of these indices that are used to categorize households in respect to their economic welfare.

The aim of this paper is to try and find out what determines whether a given household is firstly poor or rich while using the binomial logit and secondly to probe into what determines a household's probability to be poorest (hard core poverty). Inherent in themselves, indices are richer in the fact that they less likely suffer from measurement errors as is the case when measuring incomes, expenditures or consumption data. Secondly, they are constructed from a set of common household asset endowments that are observable and respondents do not find them cumbersome to report (Booysen et al., 2008). Thirdly, indices can show long run welfare effects as opposed to expenditure or consumption data (Filmer and Pritchett, 2001) in that, a household that reports ownership of tillable land can arguably be said to have better long run welfare effects than just having reported high expenditure in the past month or so. We therefore sought to answer these questions;

(i) What are the likely determinants of household welfare?
(ii) What is the probability associated with households being considered poorest?

Following the famous works of (Filmer and Pritchett, 2001), the use of DHS has been wider where studies have attempted to unpack welfare relationships and other economic variables such as health care. While showing the relationship between enrolment in schools and household welfare, (Filmer and Pritchett, 2001) use asset index from DHS data to show that in the absence of expenditure data, relationships can still be derived. In some of their earlier works they categorically show that there exist deviations in education attainment among households with different asset rankings in four countries examined: Pakistan, Nepal, Indonesia and India. In analysing poverty in nine countries in Africa, (Sahn and Stifel, 2000) employ the DHS data by constructing an asset index using the principal component analysis approach. Among other users of DHS data is (Booysen, 2002) in the study on poverty analyses done in South Africa. The study uses an asset index to compare welfare among households in South Africa. Where unemployment is rampant, it is likely that income or expenditure data may not fully represent long run welfare effects for households. Insurmountable evidence is in the empirical domain that asset indices can be used largely to avert the problems confounded in income, expenditure or even consumption data. This index is handy even in discrete choice modelling where latent variables can be studied to aid in revealing probabilities of what would drive units of analyses to either one extreme of poverty or the other. In Kenya studies have largely relied on expenditure and consumption data. (Mwabu et al., 2002) estimated poverty determinants using a linear regression model to identify that the household's economic activity, household size, household location (rural vs urban), education level of household head and livestock endowment explained significantly, the economic welfare of households. Using a discrete choice model (Nyaboke, 2000) estimated poverty in Kenya employing the Welfare Monitoring Survey data of 1994. The study took into account livestock unit, the size of household, the economic activity, and water source and off-farm employment as explanatory variables and found almost all of them as important determinants of poverty. Even though there exists sufficient literature on poverty analysis, very few are inspired to unravel the determinants of poverty among households in an asset index approach. Policy makers and households must be clear in relation to what needs to be done in order to win the fight against poverty. An analysis of this nature is therefore timely and comes in handy.

Methodology

Binomial Model

We start by indicating that households in the middle, rich and richer categories are considered "rich" while those poor and poorest are taken as "poor" in the binary case. Under this, both the linear probability model and the binomial logit are estimated. Getting the estimates of the linear probability model was fundamentally not the goal of this study. The LPM has inherent difficulties where probabilities can explode outside the reasonable probability limits while the error term in this specification is inherently heteroscedastic. However, it has the ability to give probability estimates similar to the average partial effects yielded from the binary Logit model. In the second stage, the study tried to determine the probabilities that a household could be considered poorest. The probit model could arguably be applicable as well even though with the logit model, we can obtain the probit estimates through conversion. For the binary case let us define the regression relationship as:

$$y^* = \sum X_i'\beta + \varepsilon_i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. (1)$$

Where $X_i' = [1, x_{i2}\ x_{i3} \dots x_{ik}]$ are household characteristics and $\beta = [\beta_1\ \ \beta_2\ \beta_3 \dots \beta_k]$ are the coefficient estimates.

From equation (1) the latent variable is unobserved where it captures whether a household is either rich or poor as below:

$$y = \begin{cases} 1\ if\ rich \\ 0\ if\ poor \end{cases} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Equations (1) and (2) help us develop the underlying probability expressions which in turn surmounts to our maximum likelihood set up as follows:

$$Prob(y_i = 1) = Prob\left(\varepsilon_i > -\sum X_i'\beta\right) \dots\dots\dots\dots\dots (3)$$
$$Prob(y_i = 1|x_i;\beta) = F\left(-\sum X_i'\beta\right) \dots\dots\dots\dots\dots\dots (4)$$

Where, F is basically the cumulative distribution function for the error term. In realizing the binomial specification given in equation (3) which varies with household characteristics we could observe the values of y. The maximum likelihood function can be set up by first writing down the density function:

$$f(y_i|x_i;\beta) = \prod_{y_i=0}[F\left(-\sum X_i'\beta\right)]\prod_{y_i=1}\left[1-F\left(-\sum X_i'\beta\right)\right]\ldots\ldots\ldots.(5)$$

In the MLE form, we can rewrite this as:

$$L = \prod_{y_i=1}[F\left(-\sum X_i'\beta\right)]^{1-y_i}[1-F\left(-\sum X_i'\beta\right)]^{y_i}\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(6)$$

From equation (4), it follows a log likelihood routine in which the functional form assumed for the cumulative distribution will depend entirely on the distribution that the error term is assumed to follow in specification (1). The logistic distribution and that of the normal case (probit) are nearly close to each other such that using of either leads to basically similar results. Furthermore, following (Takeshi, 1981), estimates for the probit case can be derived from the logit parameters thus pointing to convenience when faced with a choice on what model to employ. By assuming a logistic cumulative distribution of ε we specify a logit model for this study with the relevant expression as follows:

$$1-F\left(-\sum X_i'\beta\right) = \frac{e^{\sum X_i'\beta}}{1+e^{\sum X_i'\beta}}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(7)$$

$$F\left(-\sum X_i'\beta\right) = \frac{e^{-\sum X_i'\beta}}{1+e^{-\sum X_i'\beta}} = \frac{1}{1+e^{\sum X_i'\beta}}\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots...(8)$$

X is a vector of household characteristics while the $\beta's$ are the coefficients in the logistic regression. These set of equations basically return the probabilities that a given household is either poor or non-poor.

Ordered Logit Model

The ordered logit approach is a clever way to analyse the latent movement of households from being poorest, poor, being at the middle, rich and finally richest. This ordering has a natural trend and therefore an ordered logit best fits the analysis.
From equation (1), we would think that the underlying observed variable in the ordered case is defined as follows:

$$f(x) = \begin{cases} 1\ if\ poorest \\ 2\ if\ poor \\ 3\ if\ middle \\ 4\ if\ rich \\ 5\ if\ richest \end{cases}$$

Holding the assumption that epsilon follows a logistic cumulative distribution, we can rewrite equation (3) as follows:

$$Prob(y_i = j|x_i) = Prob(\alpha_{j-1} < X_i\beta + \varepsilon \leq \alpha_j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(9)$$

We can rearrange (9) to have:

$$Prob(y_i = j|x_i) = Prob\big(X_i\beta - \alpha_j \leq -\varepsilon < X_i\beta - \alpha_{j-1}\big) \ldots\ldots\ldots\ldots..(10)$$

Basically being the window between the cumulative distributions:

$$F\big(X_i\beta - \alpha_{j-1}\big) - F\big(X_i\beta - \alpha_j\big)$$

Based on this, the likelihood function can be maximized in the normal way and can be solved numerically by iteration. This way we obtain the likelihood estimates of the model.

Data Issues

The data is that of the Kenya Demographic and Health Survey of 2008. The survey collects data on household demographics and health status of household members in addition to asset holdings. Constructed through the Principal Component Analysis, the DHS wealth index variable assigns scores to households based on their asset and infrastructural access endowment. The variables (assets) employed in the computation of the wealth index are available on request from DHS. The wealth index is used to create a polychotomous variable that we employed both in the binary and ordered logit models. We created a binary variable that distinguishes between poor and rich households. In the ordered logit, we employed the original wealth variable (as captured in the DHS recode file - hv270).

The DHS used the national master sample maintained by the Central Bureau of Statistics in the first stage of the sampling design to select 400 clusters, 197 urban and 203 rural. From these clusters, desired household samples were taken using a systematic sampling approach. The number of observations in DHS household file sum up to 9,057. The descriptive statistics based on the wealth variable show that 19.62% of households are ranked poorest, 15.03% are poorer, 16.43% are in the middle, and 18.79% are richer while about 30.13% are richest. We did systematic cleaning of the data, observing every variable of interest individually and across others in the aim of ensuring they stand empirical and reality arguments.

On the age variable, we observed that seven household heads were younger than 18 years. Kenya considers individuals less than this age as juvenile and therefore do not hold any legal/social responsibilities. In normal circumstances they would not be expected to be household heads. Observing every of this seven households individually, we found out that they were the oldest of all captured members and without further information other than the DHS, it proved difficult to drop them.

Table (1) describes variables used in this study and their definition in the regression model. Note that the means for the categorical variables have not been included in the descriptive statistics as that would create interpretation difficulties following the overlay of table (1).

Table 1: SUMMARY STATISTICS AND DEFINATION OF VARIABLES

Variables	Variable name	Mean
Poverty	Welfare Index	
Household size	HHsize	4.18453
Age of HH head	Age & Age2	43.81464
Gender of HH head	Male==1	0.662471
Marital Status	Marital Categories	-
Education years of HH head	Education	7.067635
Type of place of Residence	Urban==1	-
Region	Post-Colonial Provinces	-

Discussion of Results

To obtain the expected results, this study assumed two sets of specifications. The dynamics surrounding the inclusion of a control for household location are subtly delicate to analyse. When we have an urban/rural dummy, it is very important to note that households have very distinctive patterns of asset holdings (Wittenberg, 2009) and therefore the computation of the asset index is vulnerable to regional correlation. Some assets are therefore correlated with the location of the household and therefore “earn” a negative loading factor while computing their individual factor scores. As such, households with these types of assets may be ranked poorer than those that have no assets altogether3. Cognitive of this fact, this study was motivated to show the results with both a regional dummy as well as a location one. The caveat here is that the results following the regional control are encouraged. The regions documented in the DHS are the colonial provinces in Kenya. These administrative divisions present a better comparison of household locality as opposed to taking into consideration whether a given household is in the rural or urban areas.

The Linear Probability Model and the Binary Logit Model

We do not dwell much on the results of the linear probability model. However, worth noting is that the LPM results are closely similar to those of the average partial effects from the logit regression. Similarly, the size of the household, years of education of the head of household, marital status and the regional dummy are all significant predictors of household poverty across models (1) and (2). The average partial effects of the logit model suggest that on average, increase in the size of the household reduces the probability that it is considered rich by about 3.5 percentage points. The years of education of the household head sufficiently prescribe a 3.7 percentage point increase in the probability that the household is rich should we hold other factors constant. The marital status of household heads was a categorical variable with four categories. The "divorced" category was not significant in predicting household poverty. This could arguably be said that not many observations under this category were captured. In Kenya, it is generally not the case to find people outwardly able to say they are divorced. It turns out that households with heads who are either currently married or widowed depict lesser probabilities of being rich relative to those with heads who have never been married (base case). Households with widowed heads unsurprisingly have the least chance of being rich at 13.3 percentage point less than the base case (never married). Households situated outside the larger Nairobi province showed lesser probabilities of being rich with those in Western province ranking the least at 67 percentage point lower than the case had they been in Nairobi.

Noticeably, the age of the household head and their gender turned out insignificant in predicting household poverty. Although the available literature shows that there exists a significant relationship between age of household head and poverty, many fail to substantiate its quadratic while others predict that age infinitely increase the probability that households are rich. Such results can hardly be supportable in practice. In this study, we presume that ages of other household members could as well influence welfare status and therefore, singling out an age of one of the household members may not give strong results altogether. Again, the measure of poverty here is an asset index as opposed to an individual's income. Female led households in general tend to have higher probabilities of being found richer than those led by males. Inconsistent with literature, this variable in this study does not explain poverty and therefore will not be discussed further. Table (2) carries the bulk of these results. In the appendix, we present the results of the same regression in table (4) controlling for whether a household is located in the rural or urban area.

Table 2:LINEAR PROBABILITY MODEL AND BINORMIAL LOGIT MODELS BY REGION

	Model 1		*Model 2*		*Average Effects*
VARIABLES	*LPM*	*Std err*	*Logit*	*Std err*	*Logit APE*
Welfare Index					
Age	0.00167	(0.00298)	0.0108	(0.0183)	0.00175
Age2	-1.99e-05	(2.91e-05)	-9.48e-05	(0.000185)	-1.53e-05
Hhsize	-0.0373***	(0.00387)	-0.218***	(0.0257)	-0.0353***
Education	0.0381***	(0.00287)	0.227***	(0.0214)	0.0367***
Male	-0.0157	(0.0200)	-0.130	-0.117	-0.0210
Currently Married	-0.0532**	(0.0267)	-0.504***	(0.177)	-0.0846***
Widowed	-0.107***	(0.0367)	-0.802***	(0.235)	-0.133***
Divorced	0.00336	(0.0489)	-0.210	(0.287)	-0.0355
Central	-0.188***	(0.0395)	-5.535***	(0.743)	-0.439***
Coast	-0.111**	(0.0539)	-5.014***	(0.781)	-0.345***
Eastern	-0.333***	(0.0408)	-6.191***	(0.747)	-0.561***
Coast	-0.415***	(0.0400)	-6.642***	(0.742)	-0.642***
Rift Valley	-0.266***	(0.0644)	-5.888***	(0.778)	-0.505***
Western	-0.445***	(0.0418)	-6.806***	(0.751)	-0.670***
North Eastern	-0.356***	(0.0449)	-6.482***	(0.794)	-0.614***
Constant	0.670***	(0.0701)	5.410***	(0.806)	
Obs	8,950		8,950		8,950
R-squared	0.331				

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The Ordered Logit

We use this part of the study to answer the second question. We sought to observe the underlying probability that a given household would be in the poorest category. About 20% of the households captured in the 2008 DHS are categorized poorest. This is substantially a worrying statistic in the advent of revived fight against poverty both in the country and globally. Households must firstly find way to access basic amenities if Kenya's developmental agenda is to be realized. It is therefore motivating to find that, which may assist in this course. For this, only marginal effects for the first outcome category are analysed. While considering an ordered logit, we were more interested in the coefficients of the marginal effects and only speak about the signs of the coefficients from the main regression. Interesting to note is that the signs of this coefficients alternate between the marginal effects and regression coefficients. This is an expected observation. We observe that the size of a household, the years of education of the head of household, their marital status and the region of residence are important determinants of poverty.

From table (3) reporting both the coefficients and the marginal effects, we find out that the size of the household increases the probability of being at the poorest category while the years of education of the household head reduce this probability all other things held constant. Households headed by individuals who have never married have a higher probability of not being at the poorest category than their counterparts even though estimates from the divorced category are not significant.

Marginally, households will increase their probability of being in the poorest category by 2 percentage point as members increase, holding other factors constant. On the other hand, an extra year of education of the head of the household reduces the chance of that household being at the poorest category by about 2.5 percentage points. This is expected as more years of education imply more qualification and hence increased chances of accessing higher wage work and ultimately ore assets. Being married or widowed increase the probability that the household will be poorest by about 6.2 and 8.7 percentage points respectively relative to heads who have never been married. It is rather counter intuitive to explain why married household heads will have households more prone to extreme poverty. One would expect that two individuals imply more sources of earnings for the household and therefore more assets. It could be the case however that most of the households have only one of the spouses fending for the entire household while the other stays back for household chores. This would have stringent effects on firstly resources available for use and secondly investments on assets. It also could be the case that married individuals increase institutional difficulties (bureaucracy) in investment decision making. Again, household with widowed heads depict highest chances of being in the poorest category as was the case in the binary logit model. Relative to households in Nairobi province, all the others have on average higher probabilities of being in the poorest cohort. Households in North-eastern province are more prone to hard core poverty with around 37 percentage point higher chances relative to those in Nairobi (base case).

The study has also included the results in which we controlled for whether a household is either in the rural or urban locations in the appendix. Even though the interpretation of those results are fundamentally in the same fashion, we do not include their implication here. Generally, it is worth noting that the characteristics that were originally important in the binomial model depict strong abilities to explain dynamics of poverty at the lowest category.

Table 3: THE ORDERED LOGISTIC ESTIMATION BY REGION

	Model 5		Marginal Effects	
Variables	*Beta*	*Std err*	*dydx*	*Std err*
Welfare Category				
Age	0.0107	0.0141	-0.00115	0.00154
Age2	-4.72e-05	0.000134	5.11e-06	1.46e-05
Hhsize	-0.188***	0.0193	0.0204***	0.00210
Education	0.232***	0.0169	-0.0252***	0.00208
Male	-0.0922	0.101	0.00992	0.0108
Married	-0.675***	0.147	0.0623***	0.0125
Widowed	-0.893***	0.175	0.0873***	0.0172
Divorced	-0.394	0.294	0.0336	0.0273
Central	-3.384***	0.426	0.103***	0.0135
Coast	-2.971***	0.493	0.0728***	0.0196
Eastern	-3.980***	0.430	0.163***	0.0169
Nyanza	-4.312***	0.429	0.205***	0.0167
Rift Valley	-3.858***	0.535	0.149***	0.0319
Western	-4.399***	0.428	0.217***	0.0153
North Eastern	-5.267***	0.555	0.356***	0.0623
Constant cut1	-5.470***	0.532		
Constant cut2	-4.242***	0.528		
Constant cut3	-3.166***	0.527		
Constant cut4	-1.748***	0.517		
Observations	8,950		8,950	

***p<0.01, **p<0.05, *p<0.1

Conclusion

This study aimed at unravelling poverty determinants in Kenya. The study employed the 2008 DHS for Kenya and particularly the household file. There are several policy considerations that can be derived from this study. Firstly, following work done by (Wittenberg, 2009), and considering that the wealth index was constructed generally for the entire sample, a caveat is put beforehand in believing the results pulled while controlling for a location dummy (urban/rural).

Nevertheless secondly, education of the head of household unsurprisingly determine household poverty. Therefore, there should be concerted efforts to invest and raise education awareness. More years of education mean higher levels of academic qualification leading to higher asset investment capabilities and hence less household poverty. Thirdly, larger families are prone to extreme poverty than smaller ones. It is therefore imperative to martial family planning initiatives that will raise awareness among the citizenry. Government may also legislate for social protection of household already deemed larger than their ability to provide basic amenities to their members. Such would be in form of increased scholarship opportunities to children from these households and affordable access to health care.

Fourthly, we find out that residing in Nairobi province somewhat places households lesser prone to poverty than other provinces. Ever since Kenya's independence in 1963 and before the new constitution was promulgated in 2010 that defined institutionalization of county governments, public investments were skewed towards Nairobi than other parts of the country. This not only denied opportunities to other regions of the country but also unfairly raised opportunities dispensable to the households around Nairobi. The new constitution marks a good turn-around of events where resources could be channelled through local county governments to spur growth in other areas and render them competitive. This way, the welfare of residents would be positively influenced. We suggest further research on poverty circumventing social mobility over time and inequality across regions and population groups.

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References

Booysen, F. (2002). Using demographic and health surveys to measure poverty – an application to South Africa. Journal of Studies in Economics and Econometrics, 26(3).

Booysen, F., Burger, R., and Berg, S. (2008). Using an asset index to access trends in poverty in seven sub-Saharan African countries. World Development, 36(6):1113–1130.

Filmer, D. and Pritchett, H. (2001). Estimating wealth effects without expenditure data – or tears: An application to educational enrolments in states of India. Demography, 38(1):115 – 132.

Miriam, O., Mwabu, G., and Manda, D. (2004). Poverty and unemployment in Kenya. Kenya Institute of Public Policy Research and Analysis, Working Paper (33).

Mwabu, G., Kimenyi, S., Kimalu, P., Nafula, N., and Kulundu, D. (2002). Predicting household poverty: A methodological note with a Kenyan example. Kenya Institute of Public Policy Research and Analysis, Discussion paper series (12).

Nyaboke, O. (2000). The determinants of poverty in Kenya. Ma thesis, University of Nairobi, Economics Department, UoN.

Sahn, E. and Stifel, C. (2000). Poverty comparisons over time and across countries in Africa. World Development, 28(12):2123–2155.

Takeshi, A. (1981). Qualitative response model: A survey. Journal of Economic Literature, Vol. 19(4).

Wittenberg, M. W. (2009). Weighing the value of asset proxies: The case of the body mass index in South Africa. A Southern Africa Labour and Development Research Unit Working Paper Number 39.

Appendix

The tables that follow present results of the binomial and ordered logit regressions while controlling for whether a household is either located in the rural or urban areas. Other than the location variable, the other household characteristics do pretty similar to the regressions reported in this study.

Table 4: LPM AND LOGIT REGRESSION MODELS WITH HOUSEHOLD LOCATION

	Model 3		Model 4		Average Effects
Variables	*LPM*	*Std err*	*Logit*	*Std err*	*Logit APE*
Wealth Index					
Age	0.00338	(0.00259)	0.0242	(0.0184)	0.00336
Age2	-3.02e-05	(2.65e-05)	-0.000169	(0.000192)	-2.34e-05
Hhsize	-0.0284***	(0.00395)	-0.192***	(0.0265)	-0.0266***
Education	0.0281***	(0.00238)	0.211***	(0.0196)	0.0293***
Male	-0.0151	(0.0166)	-0.166	(0.108)	-0.0231
Married	-0.0532*	(0.0315)	-0.676***	(0.236)	-0.102***
Widowed	-0.122***	(0.0413)	-1.105***	(0.289)	-0.160***
Divorced	-0.0345	(0.0352)	-0.695***	(0.239)	-0.105***
Urban	0.492***	(0.0344)	3.808***	(0.282)	0.560***
Constant	0.254***	(0.0647)	-1.289***	(0.430)	
Obs	8,950		8,950		8,950
R-squared	0.419				

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: THE ORDERED LOGISTIC ESTIMATION BY HOUSEHOLD LOCATION

	Model 6		Marginal Effects	
Variables	*Beta*	*Std err*	*dydx*	*Std err*
Welfare Category				
Age	0.0267**	0.0127	-0.00297**	0.00144
Age2	-0.000124	0.000124	1.38e-05	1.39E-05
Hhsize	-0.162***	0.0185	0.0181***	0.00207
Education	0.225***	0.0144	-0.0250***	0.00188
Male	-0.166*	0.0919	0.0182*	0.0101
Married	-0.833***	0.196	0.0748***	0.0138
Widowed	-1.153***	0.215	0.113***	0.0179
Divorced	-0.843***	0.204	0.0759***	0.0193
Urban	3.519***	0.272	-0.182***	0.0115
Constant cut1	-0.877**	0.366		
Constant cut2	0.377	0.373		
Constant cut3	1.561***	0.398		
Constant cut4	3.415***	0.453		
Observations	8,950		8,950	

Standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1