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Heterogeneous Credit Impacts of Healthcare Spending of the Poor in Peri-urban Areas, Vietnam: Quantile Treatment Effects Estimation

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Abstract

Quantile Treatment Effects are estimated to study the impacts of household credit access on health spending by poor households in one District of Ho Chi Minh City, Vietnam. There are significant positive effects of credit on the health budget shares of households with low healthcare spending. In contrast, when an Average Treatment Effect is estimated there is no discernible impact of credit access on health spending. Hence, typical approaches to studying heterogeneous credit impacts that only consider between group differences and not differences over the distribution of outcomes may miss some heterogeneity of interest to policymakers.

JEL Classification

C21, I19

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credit

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1. Introduction

The impacts of access to credit on poor household's consumption and health have been widely studied (for example, Coleman 1999, Nguyen 2008, Pitt *et al*. 2003 and Pitt and Khandker 1998). However, the literature concentrates on finding average treatment effects (ATE), which assume that all of the treated households get the same impact from program participation. Studies in other settings show that treatment effects can vary widely, not only across sub-groups but also along the distribution of outcomes (Bitler *et al*. 2006, 2008; Djebbari and Smith 2008).

This evidence of varying treatment effects is not just an econometric curiosity; it also accords well with what may interest policymakers. For example, finding that a credit program had much larger impacts for male borrowers would likely prove influential if policy makers are interested in closing gender gaps. Hence, a theme in the literature evaluating impacts of credit is to compare average treatment effects for sub-groups defined by observable characteristics (for example, age, education and gender). But the similarly interesting comparison of whether the impact is the same along the outcome distribution, such as for households with already high consumption versus those with low consumption, or already high healthcare spending versus the low spenders, is rarely done. This sort of heterogeneity in treatment effects can be studied using a Quantile Treatment Effects (QTE) estimator.

In this note we report QTE estimates of the impact that access to credit has on the healthcare spending of poor households in peri-urban Vietnam. We use a survey designed by the authors and applied to a sample that are all under the urban poverty line.[1] Hence, in typical approaches to studying heterogeneity in treatment effects this sample would be one identifiable sub-group, who would have an average treatment effect estimated and assumed to apply to all members of the group. Our results show that such an approach hides considerable within-group heterogeneity in the treatment effects.

The remainder of this note is organized as follows. The next section describes the data collection and estimation framework. The empirical results are reported in section 3, and the final section concludes.

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1 Set at six million Vietnam Dong per person per year, which is equivalent to just under US$1 per day.

2. Data and Analytical Framework

A survey of 411 borrowing and non-borrowing households was conducted from March to May 2008 in peri-urban areas of District 9, Ho Chi Minh City (HCMC) Vietnam.[2] Since our focus is on microcredit impacts on poor households, our sample was selected from poor households whose income per capita was below the HCMC general poverty line of six million Vietnam Dong per year. We use two-step sampling, first selecting wards and then households. The number of successfully interviewed households accounts for 25 percent of the total number of poor households in each of the selected wards in the district.

We use a Quantile Regression (QR) estimator, which examines the effects of the regressors on the dependent variable at various points on the conditional distribution of responses (for example, at the 25th and 75th percentiles). The model specifies the θ^{th} – quantile ($0< \theta <1$) of conditional distribution of the dependent variable, given a set of covariates x_i, and assume that residual distributions of each quantile are normal distributed, so we have:

$$Q_\theta(y_i \mid x_i) = \alpha_\theta + x_i.\beta_\theta \tag{1}$$

where y_i is the outcome of interest (the budget share for healthcare in this case) for household i, x_i is a set of explanatory variables including an indicator for credit participation, and variables measuring the household head's sex, age, marital status, and education, along with household size, household expenditure, initial income and assets, and location of the dwelling. The treatment variable of interest is credit participation which equals one if a household had received any loans in the 24 months prior to the survey and zero otherwise. A total of 304 households were borrowers, and 107 households were non-borrowers under this definition. The estimator (equation 1) is the solution to the following minimization problem (see Cameron and Trivedi 2009):

$$Q(\beta_\theta) = \min_\beta \sum_{i=1}^{n} \left[\left| y_i - X_i\beta_\theta \right|\right] = \min\left[\sum_{i:\, y_i \geq x_i\beta} \theta \mid y_i - x_i\beta_\theta \mid + \sum_{i:\, y_i < x_i\beta} (1-\theta) \mid y_i - x_i\beta_\theta \mid\right] \tag{2}$$

In other words, this is the solution to a problem where the sum of the weighted absolute value of the residuals is minimized. As θ is increased, the entire distribution of outcome y is traced, conditional on x_i. We estimate β_θ for a particular θ^{th} quantile of distribution rather

[2] HCMC has 24 Districts. District 9 is the 15th largest, with a population of 227,816 (in 2008).

than β. If we estimate β for θ, then much more weight is placed on prediction for observations with $y \geq x_{i.}\beta$ than for observations with $y < x_{i.}\beta$ (i.e. 1-θ).

When quantile regression is adapted to investigate heterogeneity in program impacts the quantile treatment effect estimator (QTE) of Heckman, Smith and Clements (1997) results. Let Y_1 and Y_0 be the outcome of interest for the treated (1) and comparison group (0). $F_1(y|x_i) = Pr[Y_1 \leq y|x_i]$ and $F_0(y|x_i) = Pr[Y_0 \leq y|x_i]$ are the corresponding cumulative distribution functions of Y_1 and Y_0 conditional on x_i. If θ denotes the quantile of each distribution, then $y_\theta(T) = \inf\{y: F_T(y|x) \geq \theta\}$, T=0, 1 (treatment status) where "inf" is the smallest value of y_θ that meets the condition in the braces. For example, $y_{0.25} = \inf\{y: F_T(y) \geq 0.25\}$, T = 0, 1. The quantile treatment effect at quantile θ^{th} is defined as $\Delta_\theta = y_\theta(T=1) - y_\theta(T=0)$, the Δ_θ is the difference between the outcome of interest for the treatment and comparison groups at a particular θ^{th} quantile. In other words, the QTE shows how the treatment effect changes across specified percentiles of the outcome distribution.

The QTE relies on the rank invariance assumption, that the relative value (rank) of the potential outcome for a given household would be the same under assignment to either treatment or comparison group (Firpo 2007). However, since outcomes for the same household may differ from one distribution to another based on observable and unobservable characteristics, bounds have to be computed for the QTE (Heckman, Smith and Clements 1997). Even without rank invariance, the QTE may still be meaningful since policymakers may be interested in the marginal distributions of the potential outcomes. In such cases, QTE is simply the difference between the same quantile of the marginal distributions of outcomes for the treated households and for comparison group households.

Heterogeneity in the outcome variable may correspond either to variation across particular sub-groups (or cohorts) in the population that would generate a local average treatment effect (LATE) or to impacts of unobservable characteristics (Angrist 2004). In this paper, we assume that we have a homogeneous population, so there are no sub-groups who would have the LATE (and for whom a particular instrumental variable might bind while it does not bind for others), and that the heterogeneity in the outcomes comes from the random errors. Since we assume it is unobservables rather than local treatment effects, causing the heterogeneity we do not necessarily need an instrumental variable estimator (which can be combined with the QTE to address bias from selection on unobservable characteristics (Abadie, Angrist and Imbens 2002). If good instruments are available, the QTE with instrumental variables (IQTE) may be more precise than the conventional IV estimator at the median (Abadie, Angrist and Imbens 2002) in addition to addressing the potential selection bias. However, in previous results with the same data used here, no good instruments are identified (Doan and Gibson 2009), so we rely on the assumption that the selection into the treatment is based on observables.

3. Empirical Results

Table 1 presents unconditional differences in monthly average healthcare expenditure (in 1,000 Vietnam Dong) and in the healthcare budget share. At all points in the distribution of healthcare spending considered here, households who were borrowers spent more on health than their non-borrowing counterparts. The households who borrowed had similar initial income to the non-borrowers, but higher current consumption (Appendix A). So, one possible reason for higher health spending might be that the same budget share generates more spending for richer households. But in fact that is not the case, the borrowing households also are devoting larger *shares* of their budgets to health at all points in the distribution.

Table 1: Monthly Healthcare Expenditure of Borrowers (B) and Non-borrowers (NB)

	Mean		25th percentile		50th percentile		75th percentile	
	B	NB	B	NB	B	NB	B	NB
Healthcare expenditure	299.67	220.84	63.17	12.08	119.67	69.67	290.42	185.00
	(6.43)	(5.31)	(1.84)	(0.61)	(3.37)	(2.26)	(7.50)	(6.06)

Notes: The budget share for healthcare in the parentheses, B is Borrowers and NB is Non-borrowers

To see whether the higher healthcare spending of borrowers across the distribution persists when we condition on explanatory variables, we estimate quantile treatment effects at the 25th, 50th, and 75th percentiles (Table 2). The table also presents OLS estimates in the final column of each panel. The explanatory variables used are listed in Appendix A. Our basic specification includes location, household size and expenditure per capita in addition to the credit participation treatment variable, while an extended specification adds the gender, age, marital status, and education of the household head, and pre-treatment values of income per capita and assets.[3]

[3] Descriptive statistics for these variables and the tests of their differences between borrowers and non-borrowers are presented in Appendix A.

Table 2: Quantile Regressions of Credit Impact on Budget Shares of Healthcare Expenditure

Explanatory Variables	Basic specification 0.25	0.50	0.75	OLS	Extended model specification 0.25	0.50	0.75	OLS
Credit dummy	0.0078	0.0060	-0.0009	0.0088	0.0093	0.0115	-0.0053	0.0114
	(0.002)**	(0.006)	(0.016)	(0.011)	(0.002)**	(0.006)+	(0.016)	(0.011)
Log size	0.0029	0.0048	0.0139	-0.0120	0.0020	0.0034	0.0061	-0.0108
	(0.0020)	(0.006)	(0.013)	(0.014)	(0.003)	(0.007)	(0.014)	(0.013)
Log PCX	-0.0021	0.0004	0.0287	0.0303	-0.0037	-0.0014	0.0140	0.0252
	(0.0015)	(0.004)	(0.01)**	(0.012)*	(0.002)*	(0.005)	(0.012)	(0.014)+
Constant	0.0110	0.0037	-0.1547	-0.1475	-0.0102	-0.0764	-0.3048	-0.3459
	(0.0114)	(0.032)	(0.063)*	(0.082)+	(0.027)	(0.052)	(0.133)*	(0.133)**

Notes: Bootstrap standard errors in parentheses with 1000 replications; + significant at 10%; * at 5%; ** at 1%. OLS standard errors are robust. Dependent variable is the budget share for health spending; Log size is the log of household size; Log PCX is monthly expenditure per capita (in log). The number of observations is 411 households. Both the basic and extended models control for location dummies. The extended model specification further controls for head's sex, age, marital status, education, and initial income per capita and assets.

In both the basic and extended specification, there is considerable heterogeneity in the treatment effects of credit on the healthcare budget share (Table 2). For households with health budget shares below the median, access to credit is associated with significantly higher healthcare spending. But for households above the median healthcare spending goes down (insignificantly) when a household is a borrower. The same pattern is observed when using the extended model specification. In neither case would these effects be apparent when using OLS.

Thus it appears that access to credit increases the healthcare budget share of households who had lower healthcare budget shares prior to their credit participation. This positive effect of credit is hidden when estimating an average treatment effect, even though the sample are for a homogenous group of urban households from one district who are all below the poverty line.

There also appears to be some heterogeneity in the effect of per capita household expenditure (used as a proxy for permanent income) on the healthcare budget share. The OLS estimates suggest that the healthcare budget share rises by about three percentage points for every one log point increase (approximately two standard deviations) in per capita expenditure. But this hides an effect (which is statistically significant in the extended specification) of the budget shares falling with higher expenditure at the 25th percentile.

4. Conclusions

Treatment effects can vary widely, not only across sub-groups but also along the distribution of outcomes. In this note we provide an example where our sample are all under the urban poverty line and would typically be considered as one identifiable sub-group, for whom an average treatment effect would be estimated. Yet we find considerable heterogeneity in treatment effects within this seemingly homogenous sample, which would be hidden if we only reported an average treatment effect.

Specifically, while OLS estimates of Average Treatment Effects show no significant effect of credit participation on healthcare budget shares, the Quantile Treatment Effects estimates show that credit has positive impacts on healthcare budget shares for households with low levels of healthcare spending. From a policy point of view, this suggests that facilitating access to credit sources may be a significant factor in improving health status of the urban poor.

Appendix A

Descriptive Statistics and *t*-values for Equal Means by Borrowing Status

Variables	Borrowers		Non-borrowers		*t*-value
	Mean	Std.Dev	Mean	Std.Dev	
Variables for basic specification					
Monthly health care expenditure	299.671	582.295	220.840	551.908	1.25
Health budget share	0.064	0.092	0.053	0.093	1.07
Household size in log	1.554	0.440	1.354	0.577	3.26**
Total monthly expenditure	4,416	2,738	3,602	2,597	2.75**
Monthly expenditure per capita in log	6.691	0.484	6.611	0.596	1.25
Location:					
Tang Nhon Phu A (Yes=1)	0.188	0.391	0.299	0.460	2.24*
Long Truong (Yes=1)	0.313	0.464	0.234	0.425	1.61
Long Phuoc (Yes=1)	0.322	0.468	0.243	0.431	1.60
Phuoc Binh (Yes=1)	0.178	0.383	0.224	0.419	1.01
Additional variables for extended specification					
Head’s sex (male=1)	0.507	0.501	0.505	0.502	0.03
Head’s education (year)	4.911	3.350	4.664	3.760	0.60
Married (yes=1)	0.648	0.478	0.607	0.491	0.74
Head’s age (year)	52.901	13.970	59.467	15.460	3.87**
Initial assets incl land and assets in log	13.183	1.243	12.977	1.667	1.17
Initial income per capita in log	8.161	0.227	8.114	0.347	1.31
Observations (households)	304		107		

Notes: t-value statistically significant at 10% (+), 5% (*), and 1% (**); assets, income, and expenditures are measured in VND 1,000. These variables are used in models in Table 2.

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