Impacts of Household Credit on the Poor in Peri-urban Areas of Ho Chi Minh City, Vietnam

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Abstract

Access to credit is universally believed to be an effective tool to help the poor out of poverty. Yet the evidence for this has not considered all settings, especially the peri-urban areas of rapidly industrialising Asian countries. In these areas human capital is the main asset of the poor, so it is important to understand the input of credit on human capital. Therefore, this thesis begins with Chapter 2 showing the importance of human capital in income generation in Vietnam during the economic transition. The thesis then examines factors affecting credit participation and credit constraints for the poor in the peri-urban areas, and investigates whether credit participation impacts the poor's education and healthcare spending and benefits their children's schooling.

Chapter 2 employs five large datasets of Vietnam Household Living Standard Surveys (VHLSS) conducted in 1998, 2002, 2004, 2006 and 2008 by Vietnam General Statistics Office (GSO) to examine the rate of return to schooling in Vietnam over the period of 1998-2008. The chapter finds that the rate of return has increased quickly during the recent economic reform and reached around 9-10 percent. The chapter clearly indicates an increasing importance of education in earnings during the later part of the economic transition in Vietnam. Therefore, human capital investment, including healthcare and education, is needed to help the poor escape poverty since they rely heavily upon labour income, especially in urban and peri-urban areas.

One of the typical solutions to improve the poor's human capital is to provide access to credit resources, however, there are many barriers blocking the poor's access to credit. Chapter 4 uses a novel dataset collected by the author from peri-urban areas of Ho Chi Minh City, Vietnam in 2008 to examine how the poor use their loans, and factors affecting their credit participation and credit constraints. The chapter finds the presence of many commercial banks in the areas does not help the poor, who rely heavily on informal credit. Loans in the peri-urban areas are mainly used for non-productive purposes, which stresses the importance of consumption smoothing motives. Further, households in more rural wards have a higher probability of borrowing than more urban households, thanks to better community relationships and interpersonal trust. Competition by borrowing neighbours adversely affects the opportunity for borrowing in urban wards where the poor households' borrowings rely more on subsidized credit funds. A closer look at specified microcredit sources reveals that household behaviours differ in each market segment. Furthermore, the poor are highly credit-constrained. Wealthier households, in terms of

asset holdings and phone possession, appear less credit-constrained. However, except in the most rural part of the study area, the likelihood of credit constraints increases with distance to the nearest banks, which suggests that supply-side intervention could help in overcoming credit constraints. Overall, the poor in urban wards are more credit-constrained because of exclusion by commercial banks and weak interpersonal trust.

Given that a sizeable fraction of the poor have participated in credit activities, there is a debate about whether microcredit has positive impacts on education and health for borrowing households. To provide evidence for this debate, Chapter 5 mainly uses the Propensity Score Matching (PSM) method to examine the impact of household credit on education and healthcare spending by the poor in the peri-urban areas. In addition to matching statistically identical non-borrowers with borrowers, my estimates also control for household pre-treatment income and assets, which may be associated with unobservable factors affecting both credit participation and the outcomes of interest. The PSM estimates show significant and positive impacts of borrowing on education and healthcare spending. However, multiple ordered treatment effect estimates reveal that only formal credit has significant and positive impacts, while informal credit does not have significant impacts.

Whether the effects of credit are homogenous across distributions of outcome variables is another question of interest. This question asks 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. Chapter 6 employs a Quantile Treatment Effect estimator (QTE) and finds heterogeneity in the impacts on household budget shares for education and healthcare.

Finally, household credit for the poor was examined and found to have a positive influence on current expenditure on education. However, to test whether the credit to the poor has longer term effects on education, in Chapter 7 there are results for estimating the impact of the credit on child schooling. Probit, Negative Binomial (NB) and PSM estimates roughly indicate no strong evidence of an effect, especially of informal credit, although formal credit may have a positive impact on child schooling.

Notes on publications

A number of working and conference papers have been produced from this thesis, and some were sent off and being reviewed for possible publication as follows:

Doan, T., Gibson, J., & Holmes, M. (2008, July). *Do returns to schooling go up during transition? Evidence from Vietnam.* Paper presented at Econometric Society of Australasia Meeting 2008 (ESAM08), Wellington, New Zealand. Retrieved from http://www.nzae.org.nz/conferences/2008/100708/nr1215395974.pdf

Doan, T., & Gibson, J. (2009). *Do returns to schooling go up during transition? The not so contrary case of Vietnam* (Working papers in Economics No 09/08). Retrieved from University of Waikato, Department of Economics website: ftp://mngt.waikato.ac.nz/RePEc/wai/econwp/0908.pdf

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Doan, T, Gibson, J., & Holmes, M. (2010, June). *Impacts of household credit on education and healthcare spending by the poor in peri-urban areas of Ho Chi Minh City, Vietnam*. Paper presented at the 6th Australasia Development Economics Workshop, the University of Western Sydney, Australia. Retrieved from http://www.adew2010.com/papers/DOAN.pdf

Doan, T., Gibson, J., & Holmes, M. (2010, July). *Does credit for the poor benefit their children's schooling? A case study of peri-urban areas of Ho Chi Minh City, Vietnam.* Paper presented at the 51st New Zealand Association of Economists (NZAE) Annual Conference, Auckland University. Retrieved from http://www.nzae.org.nz/conferences/2010/Papers/Session1/Doan__Does_Household_Credit_to_the_Poor.pdf

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Doan, T., & Gibson, J. (2010). The returns to schooling in Vietnam during economic transition: Does rate of return to schooling reach its peak? *Economics Bulletin, 30*(2), p.A2.

Doan, T., Gibson, J., & Holmes, M. (2010). *What determines credit participation and credit constraints of the poor in peri-urban areas, Vietnam?* (MPRA Paper No. 27509). Retrieved from Munich Personal RePEc Archive website: http://mpra.ub.uni-muenchen.de/27461/1/MPRA_paper_27509.pdf

Doan, T., Gibson, J., & Holmes, M. (2010). *What determines credit participation and credit constraints of the poor in peri-urban areas, Vietnam?* (MPRA Paper No. 27509). Retrieved from University Library of Munich archive website: http://ideas.repec.org/p/pra/mprapa/27509.html.

This paper was also presented at Workshop on Development in the Mekong region, February 2011 at the University of Waikato http://wms-soros.mngt.waikato.ac.nz/nr/econconf/includes/docs/day02.pdf

Dedication

This thesis is dedicated to my mother, who was called to rest during the course of this journey, and to my father, my dear wife and son.

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List of Abbreviations

ASA: the Association for Social Advancement

ATT: Average Treatment Effect on the Treated

ATTK: Average Treatment Effect on the Treated with Kernel matching estimator

ATTR: Average Treatment Effect on the Treated with Radius matching estimator

BRAC: the Bangladesh Rural Advancement Committee

BRDB: the Bangladesh Rural Development Board

CGAP: the Consultative Group to Assist the Poor

CIA: Conditional Independence Assumption

FDI: Foreign Direct Investment

GSO: Vietnam General Statistics Office

HCMC: Ho Chi Minh City (Vietnam)

HEPR: Hunger Eradication and Poverty Reduction

IFC: the International Financial Corporation

IMF: the International Monetary Fund

IV: Instrumental Variables

JCSF: Job Creation Support Fund

LP: Long Phuoc ward

LT: Long Truong ward

MNL: Multinomial Logit Model

NB: Negative Binomial Model

NGO: Non-Government Organisation

OLS: Ordinary Least Squares

PB: Phuoc Binh ward

PCF: People’s Credit Fund

PSM: Propensity Score Matching

QTE: Quantile Treatment Effect estimator

ROSCAs: Rotating Saving and Credit Associations

SURE: Seemingly Unrelated Regression Estimator

TNPA: Tang Nhon Phu A ward

UNDP: United Nations Development Programs

VBARD: Vietnam Bank for Agriculture and Rural Development

VBSP: Vietnam Bank for Social Policies

VHLSS: Vietnam Household Living Standards Survey

VND: Vietnam Dong

WB: the World Bank

Chapter 1: Introduction

"Lasting peace cannot be achieved unless large population groups find ways in which to break out of poverty. Microcredit is one such means. Development from below also serves to advance democracy and human rights."

Norwegian Nobel Committee, October 2006

1.1 Introduction

Since Professor Mohammad Yunus and the Grameen Bank won the Nobel Peace Prize in 2006 for their contribution to poverty reduction through microcredit programs, there has been a huge public interest in microcredit. Microfinance, of which microcredit is the main part but also including other micro financial services such as insurance and savings vehicles, has become a popular approach and a powerful tool in poverty alleviation strategies in developing countries (Microcredit Summit, 2004).

The first Microcredit Summit in February 1997 launched a nine-year campaign to reach 100 million of the world's poorest households by 2005. In fact, microcredit has reached even more clients, rising from 13.5 million families in 1997 to about 155 million families by the end of 2007 (Microcredit Summit, 2009). By the end of 2007, supposing that each household has an average of five members, then microcredit has affected about 775 million people on the earth.

However, the statistics may be underestimated as information on informal credit, which is a part of microcredit, is not readily available. It is believed that a majority of people in developing countries borrow from the informal credit sector, such as relatives, friends, neighbours, moneylenders, and others (Banerjee & Duflo, 2010). For example, in a survey of 13 developing countries, Banerjee and Duflo (2007) find that only about 6% of the funds borrowed by the poor came from the formal credit sector. Another example; in Bangladesh about 75% of rural households borrowed from the informal credit sector in 1989,[1] and in another surveyed village in India, 86% of total loans and more than 60% of the total credit amount were from the informal credit sector (Ramachandran & Swaminathan, 2001). It therefore implies that a large proportion of the poor and low income households seek credit resources from the informal credit sector. Both the

[1] www.banglapedia.org/httpdocs/HT/I_0066.HTM

unrecorded informal credit borrowers and the number of clients reported by the Microcredit Summit would have amounted to hundreds of millions of households.

In Vietnam, microcredit has continued to be of great importance in providing credit to the poor and low income households. In 2007, there were about 20 million households in Vietnam, but the number of active microfinance institution clients was about 7.1 million, of which 4.6 million were from the poorest households (Microcredit Summit, 2009).[2] A sizeable fraction of households, especially the poor, continued to borrow from informal credit providers, although the percentage decreased from 73% of household's loans in 1993 to about 34% in 2006 (McCarty, 2001; UNDP, 1996; VHLSS, 2006).

Furthermore, the Vietnam Bank for Social Policies (VBSP), the Job Creation Support Fund (JCSF), People's Credit Fund (PCF), and other political social organizations (e.g. Women Union) have typically provided preferable or subsidised loans. All loans from these providers, and from informal lenders, such as private moneylenders, relatives and friends and other informal sources, are often small and could be considered microcredit.[3] Taking all the borrowers of these providers/sources together adds up to more than 50% of total borrowing households.

Microcredit, including formal and informal sectors has substantially provided credit or small loans to the poor and low income households worldwide including Vietnam, but the effects of microcredit on the poor remain debatable. Therefore, this thesis seeks to empirically study the impacts of microcredit on education and healthcare of the poor in Vietnam.

1.2 Problem statement

Existing literature on the impacts of microcredit has provided ambiguous or non-robust evidence of impacts. Many studies claim positive impacts. For example, the highly cited studies (Pitt & Khandker, 1998; Khandker, 2005) show that microcredit has positive impacts and helps the poor out of poverty, especially Gremeen Bank clients. Other studies by Islam (2007, 2008), Nguyen (2008), Quach, Mullineux, and Murinde (2005), and Rahman, Mallik and Junankar (2007) also find positive impacts on microcredit borrowers' welfare. On the other hand,

[2] Suppose one client is in each borrowing household, so about one third of households in Vietnam borrowed from microcredit sources.
[3] Microcredit and household credit are used interchangeably in this study

many other studies are sceptical of the impact of microcredit participation on borrowers' welfare, finding that microcredit borrowers are not better off (Coleman, 1999, 2006; Morduch, 1998, Roodman & Morduch, 2009). Even some studies of randomised control trials, such as Banerjee, Duflo, Glennerster and Kinnan (2009), Roodman (2009), and Rosenberg (2010) provide limited evidence of the impacts. Thus, evidence of microcredit impacts is mixed.

Moreover, the existing literature often considers effects of credit programs or formal credit but does not consider effects from informal credit. Besides borrowing from programs or the formal credit sector, a sizeable fraction of poor people also borrow from informal sources such as friends, relatives, neighbours, moneylenders and other informal credit sources, so the existing estimated effects would also include informal credit effects. Failing to take into account the impact of informal credit separately from formal credit will cause biased estimates.

A further feature of the literature is that most analyses are for rural areas, but rural areas hold a declining share of the world's poor (Haddad, Ruel, & Garrett, 1999; Mooya & Cloete, 2007; Ravallion, Chen, & Sangraula, 2007). In fact, while the poor in developing countries often migrate to cities, they tend to reside in peri-urban areas since city centres are too expensive for them to live. In peri-urban areas, credit often supports consumption expenditure such as healthcare, school fees and food, rather than production as in rural areas. This sort of consumption affects human capital formation. Moreover, the poor often live on labour income in peri-urban areas where human capital is the most important household asset and more important than in rural areas since returns to human capital (education) is higher in urban and peri-urban areas than in rural areas (Goetz & Rupasingha, 2004; Sicular et al, 2007). However, most of the existing literature has focused on the impacts of microcredit on rural areas and for production purposes.

Therefore, what is needed is comprehensive research showing the links between credit access and human capital (in terms of education and health). Moreover, to the extent that links between human capital and earnings strengthen in transition economies, the economic impacts of credit access operating via human capital investment will become more important over time.

In summary, the existing research on the impact of microcredit fails to reach a consensus conclusion, fails to consider the impact of informal credit, fails to consider the impacts of microcredit for urban areas, and fails to establish a link between microcredit access and human capital, and then between human capital and earnings. These shortcomings prompt the current thesis to provide empirical evidence on how microcredit, including the informal credit, impacts the poor in terms of human capital investment in peri-urban areas.

1.3 Significance of the research

Vietnam has experienced impressive economic growth and poverty reduction over the last 20 years. The real GDP per capita has increased remarkably from US$98 in 1990 to more than US$1,000 in 2009 (IMF, 2010). Poverty incidence has declined sharply, from 75% in the middle of 1980s to 58% in 1993 (VHLSS, 1993) and to 15.5% by 2006 (VHLSS, 2006). These achievements resulted from macroeconomic policies favouring adjustment to a market economy and from policies targeting the poor.

In Vietnam, poverty is universally attributed to insufficient access to capital and low investment in education (Le & Tran, 2005; McCarthy, 2001; VDR, 2004; WB, 1998). To alleviate poverty, the Vietnamese government has recently introduced microcredit programs to alleviate poverty and vulnerability for the poor through the Hunger Elimination and Poverty Reduction program (HEPRF), the Vietnam Bank for Social Policies (VBSP), Vietnam Bank for Agriculture and Rural Development (VBARD), and Job Creation Support Fund (JCSF). However, there has been no officially reliable study on the program impacts by any government organizations. Nhu Trang (2005) observed that the efficiency of the programs seems to be rather low in terms of meeting credit demand and long-run stability because a considerable fraction of households have been continuing to seek informal credit sources regardless of their usury interest rates. Moreover, microcredit institutions need subsidies from government funds. For instance, in order to survive the VBSP has received government subsidies for interest disparity and operation costs equivalent to more than 51% of its annual revenue.[4]

However, there are only a few studies on the impacts of credit on household consumption in Vietnam. These few studies focus only on rural areas and never consider impacts on child schooling, or spending on education and healthcare, which are important factors affecting human capital formation and productivity of household members, as well as sustainable poverty reduction (Nguyen, 2007;

[4] Annual report of VBSP, available at www.vbsp.org.vn/Icon_BCTN/36.gif

Nguyen, 2008; Quach et al, 2005). Furthermore, to the best of my knowledge, no single impact study of microcredit for peri-urban or urban areas in Vietnam exists.

1.4 Objectives of the research

The thesis has six objectives:

i. To examine how the rate of return to schooling has changed in Vietnam during the economic transition period, and to provide evidence of the increasing importance of education in earnings and poverty reduction. The objective enables us to understand the growing importance of human capital formation in Vietnam.

ii. To determine important factors affecting the probability of credit participation and credit constraints for the poor in peri-urban areas of Ho Chi Minh City, Vietnam.

iii. To estimate impacts of household credit on education and healthcare spending of the poor.

iv. To examine whether the impacts of household credit on household budget shares for education and healthcare are heterogeneous amongst the peri-urban poor population.

v. To examine the impact of household credit on human capital formation among the poor through child schooling outcomes.

vi. To determine the impacts of different sources of household credit on the poor.

1.5 Research questions

To achieve the above objectives the thesis will answer the following research questions:

- Has education become a more important driver of earnings in Vietnam during economic transition from centrally planned economy to a market economy?
- Who are the microcredit clients and what determines household credit participation and credit constraints in the peri-urban areas?
- What are the impacts of household credit on healthcare and education expenditure?
- Are the microcredit effects heterogeneous across outcome distributions of household budget shares?
- Does microcredit really help the schooling of poor children?

1.6 Background

1.6.1 Urban population growth in Vietnam, the Southeast region and Ho Chi Minh City

Poverty in developing countries is increasingly urban, with the poor urbanising more quickly than the population as a whole. Moreover, in 2008 humanity passed the threshold of more than 50% of the world population in urban areas (United Nations, 2007). These trends are also apparent in Vietnam, with the share of urban population rising from 23.7% in 1999 to 29.6% in 2009 (GSO, 2010). In the period 1980-1985 (before the economic reform), migration only contributed 28% of the urban population growth, but since the reform era immigrants to urban areas have contributed 50% and 62% of the urban population growth in the periods 1990-1995 and 2000-2005 (Euromonitor International, 2005). Over the period 1999-2009, 77% of the population growth in Vietnam is in urban areas. The urban population growth rate is 3.4%/year, 8.5 times as high as that of rural areas (0.4%/year), with this higher growth mainly due to rural-urban migration (GSO, 2010).

Within Vietnam, the Southeast region has experienced the highest recent population growth (3.2%/year) due to the substantial migration to this region. The key destinations of immigrants in the Southeast region, which includes Ho Chi Minh City (HCMC) and 5 provinces of Dong Nai, Binh Duong, Binh Phuoc, Baria-Vung Tau and Tay Ninh, are Binh Duong, HCMC and Dong Nai. Their inward migration rates are 340 per thousand, 136 per thousand, and 66 per thousand, respectively (GSO, 2010, p. 5-6). Within the Southeast, following Binh Duong's population growth of 7.3% per year, HCMC is not only the largest city, but also the second fastest growing population in Vietnam (3.5%/year) during the last 10 years (GSO, 2010, p. 35). In addition, the fact that the fastest growing province of Binh Duong is adjunct to HCMC makes HCMC and its neighbouring provinces the most dynamic population areas in Vietnam. The main reason for migration to the region is to seek economic opportunities in non-agricultural sectors. Most migrants to the region arrive in Binh Duong, HCMC and Dong Nai (these destinations have 43 industrial parks and export-processing zones and account for one third of total accumulated FDI capital since Vietnam implemented the FDI law in 1988) to seek employment (GSO, 2010, p. 77 & 81).[5&6]

In contrast, rural areas hold a declining share of the world's poor (Haddad, Ruel, & Garrett, 1999; Mooya & Cloete, 2007; Ravallion, Chen, & Sangraula, 2007), which is also evident in Vietnam. Poverty sharply declined over the period 1998-2008 from 37.4% to 14.5%. Urban poverty rate has been declining from 9.5% in 1998 to 3.3% in 2008, but the urban areas have a rising share of poverty, from 5.99% in 1998 to 6.63% in 2008 due to fast population growth in urban areas during the same period (VDR, 2010; VHLSS, 2008; GSO, 2010). The poverty is becoming more urban in Vietnam, and thus study of urban poverty is becoming significant for poverty reduction policy in Vietnam.

1.6.2 Fast urbanisation, employment and poverty in peri-urban/urban areas

Peri-urban and urban poor people often depend more on wage-paid employment and cash incomes (Bryld, 2003; Rakodi, 1995), but less on agricultural activities to earn because of the declining arable land due to urban enchroachment (Midmore & Jansen, 2003). Furthermore, the higher cost of living and market reliance could result in a slower pace of poverty reduction in peri-urban and urban areas (Ravallion et al, 2007). Thus, the higher unemployment rate in the areas will result in unstable livelihoods and imperfect consumption smoothing (Meng, 2003). Moreover, poverty in urban and peri-urban areas is likely to concentrate on immigrants (Rashid, 2000, p. 242).

Urbanisation has reduced agricultural land in HCMC, from 95,799 hectares of arable land for annual crops in 2000 to 44,441 hectare in 2009.[7] In my study area (District 9) agricultural land fell from 5,661 hectares to 332 hectares during the same period. This reflects the substantial population growth rate,[8] establishment of new enterprises (from about 400 in 1997 to 1,658 enterprises by 2006),[9] and the construction of HCMC High Tech Park (about 1,000 hectares).[10] As a consequence of the arable land decline, the peri-urban poor in HCMC rely more on seasonal and unstable jobs such as street vendors, construction workers

[5] Vietnam has 249 industrial parks and processing zones by the end of 2009, see at http://www.khucongnghiep.com.vn/news_detail.asp?id=159&IDN=2247&lang=vn
[6] See at http://www.gso.gov.vn/default_en.aspx?tabid=471&idmid=3&ItemID=9937
[7] See at http://www.pso.hochiminhcity.gov.vn/so_lieu_ktxh/2009/nong_nghiep/0507.htm
[8] See at http://www.pso.hochiminhcity.gov.vn/so_lieu_ktxh?ID=2000
[9] See at http://www.quan9.hochiminhcity.gov.vn/Office_Infor.asp?Cat=9&ID=192
[10] See at http://www.shtp.hochiminhcity.gov.vn/Sites/Web/NewsDT.aspx?PostID=916&CateID=68

and unskilled factory workers (VDR, 2004). This indicates that the poor depend more on labour incomes, so adverse shocks which cause loss of working members such as illness, injury, accidents and death, and limited access to quality social services will lead to unstable livelihoods (VDR, 2004, p. 110). Therefore, such approaches as improving human capital (education and health) and facilitating access to social and financial services are needed to mitigate vulnerability and effectively eliminate poverty.

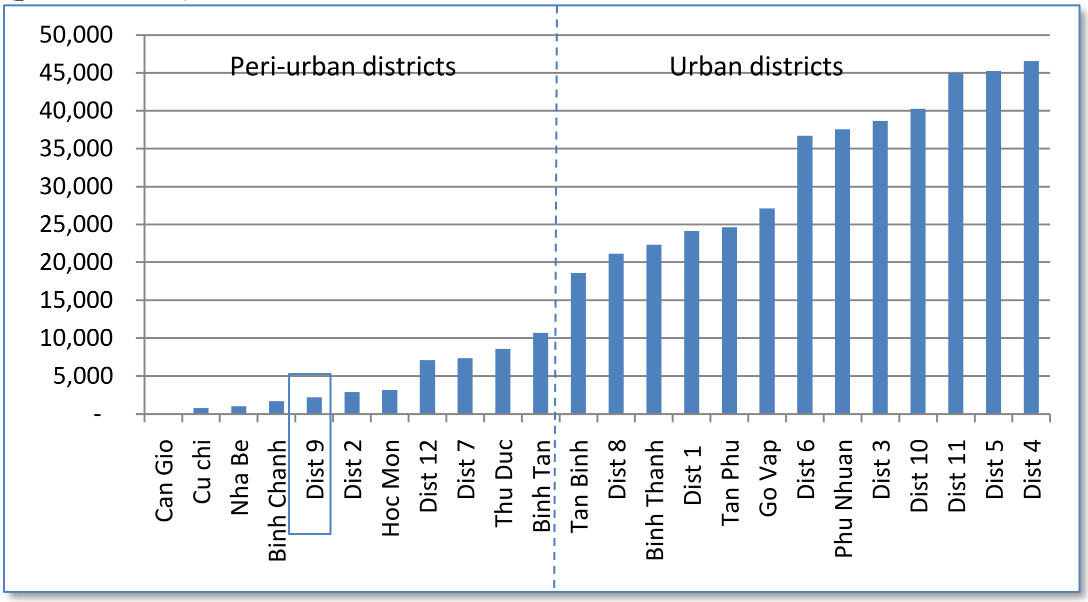
1.6.3 What defines peri-urban areas in HCMC?

The term peri-urban is widely used in the literature, but there is no a standard definition. OECD (1979, p. 10) states "the term peri-urban cannot be easily defined,…it is a name given to the grey area which is neither entirely urban nor purely rural in the traditional sense; it is at most the partly urbanised rural areas". FAO (2001) defines peri-urban areas as being associated with urban city centres, lower population density, geographical proximity to a city, urban growth and expansion. Overall, there are three main features of peri-urban areas: first, they are often associated with the urban fringe or surrounding areas of a city. Second, peri-urban is different from urban in terms of socio-economic conditions; especially infrastructure is less developed than urban areas (FAO, 2001; Norstrom, 2007, p. 5). Third, peri-urban areas have both traditional (rural) and modern (urban) social characteristics (Clough, 1996). Moreover, peri-urban areas are closely linked to the urbanisation process. In peri-urban areas, population size and density, and non-agricultural labour force are increasing, result from rural-urban migration to seek non-agricultural employment (Iaquinta & Drescher, 2000).

There are no criteria to define peri-urban areas in HCMC. To classify urban and peri-urban districts, I use the economic structure (agricultural and non-agricultural contribution in district GDP), proximity to the city centre, and population density (Figure 1.1) and population growth.[11]

[11] See at http://www.pso.hochiminhcity.gov.vn/so_lieu_ktxh/2000/Dan_so_va_lao_dong/0203.htm/view, and http://www.pso.hochiminhcity.gov.vn/so_lieu_ktxh/2009/Dan_so_va_lao_dong/0201.htm/view

Figure 1.1: Ho Chi Minh City population density by district in 2009 (persons/km²)



Accordingly, Can Gio, Cu Chi, Nha Be, Binh Chanh, Hoc Mon, Thu Duc, Binh Tan and Districts 2, 7, 9, 12 are peri-urban districts (11 districts). These districts have a certain agricultural contribution in their GDP and have a lower population density, from 104 to about 10,000 people/km^2. These districts are also on the urban fringes, and have experienced fast population growth, from 32% to 150% (depending on districts) over the period 1997-2009. My study district (District 9), which has population growth rate of 72%, belongs to the peri-urban district group. The other 13 districts which have a very high population density, from 18,600 to 46,500 people/km^2, are classified as urban districts. Almost all urban districts have negative or low population growth rates over the period 1999-2009.

1.7 Research methods and data sources

The thesis applies various econometric methods to two sources of data to achieve the research objectives.[12] *First*, to achieve the first objective of studying changing returns to schooling, datasets from five rounds of Vietnam Household Living Standard Survey (VHLSS) conducted by Vietnam General Statistics Office (GSO) in 1998, 2002, 2004, 2006, and 2008 are used. The samples are representative for the national level of Vietnam. The surveys offer all necessary information to estimate the returns using the Ordinary Least Squares (OLS) and Heckman selection model.

[12] Detailed discussions on econometric methods are presented in Chapters 2, 4, 5 , 6 and 7.

Second, for the remaining objectives of the thesis, I conducted a field survey. A sample of 411 borrowing and non-borrowing households was interviewed in early 2008 in the peri-urban District 9, Ho Chi Minh City (HCMC) Vietnam.[13] Since my focus is on microcredit impacts on poor households, the sample was selected from a list of poor households whose initial income per capita was below the HCMC general poverty line of VND 6 million (approximately US$1 per day).[14] The target sample size was set at 500 households, including 100 reserves, to achieve a realised sample of 400 (Appendix 1.1). In fact, 411 households were successfully interviewed, accounting for 26% of the total number of poor households in each of the selected wards in the district. The interviewed sample provides 304 borrowing households and 107 non-borrowing households, with 2,062 members, 955 (46.3%) males and 1,102 (53.7%) females, including 483 school-aged children. The sample is likely to be representative for the poor group whose initial income per capita is below the poverty line at the survey time in the district but will not be representative for Ho Chi Minh City nor for Vietnam.

The survey was designed to collect data on household and individual demographic-economic variables, commune characteristics, household durable and fixed assets, child schooling and education expenditure, healthcare, food, non-food, housing expenditure, and borrowing activities. I also utilised GPS receivers to collect data on locations of households and facilities in order to measure distances from each household to facilities.

The surveyed areas are located in the most dynamic region, Ho Chi Minh City (HCMC), in Vietnam. The city is the biggest economic-financial centre in the country; it accounts for only 6.6% of the country's population in 2005 but one third of GDP. The city economy has recently been growing at above 10% per annum. [15]

The surveyed district is the 5th lowest population density district, and one of the peri-urban districts of HCMC. When it was established in 1997, the district relied heavily on agricultural production, but its economic structure has changed

[13] HCMC has 24 Districts. District 9 has the 5th lowest population density, with a population of 227,816 (in 2008). For its position, see Figures 1.2 and 1.3 at the end of this chapter.
[14] The list was provided by the District Department of Labour, Invalids and Social Affairs.
[15] See at http://www.hochiminhcity.gov.vn/gioithieu/lists/posts/post.aspx?Source=/gioithieu/&Category=Gi%E1%BB%9Bi+thi%E1%BB%87u+chung&ItemID=9&Mode=1

drastically due to current fast industrialisation and urbanisation. The average growth rate of industrial production and services has been very high for the period 1997-2008, namely 24.7% and 28.1% per year respectively. The total number of enterprises, approximately 400 in 1997, increased to 1,658 in 2006.[16] In addition, the district population growth rate is very high; it increased 59% over the period 1997-2008. Population density within the surveyed district in 2008 is heterogeneous. Some wards are very highly populated e.g. Phuoc Binh (PB) (18,981 people/km^2), Tang Nhon Phu A (TNPA) (6,546 people/km^2), while others are relatively low, e.g. Long Phuoc (LP) (300 people/km^2), Long Truong (577 people/km^2). The main economic activities of the district are non-farm economic activities such as industrial production, construction and services (see Appendices 1.2 and 1.3). For my sample, 72% of household heads are small traders, housewives, casual workers, factory workers and the jobless.

1.8 Structure of the thesis

The current thesis is organised as follows:

Chapter 2 discusses the returns to schooling in Vietnam during the economic transition. This chapter will explain the increasing importance of human capital in earnings during the economic transition and how education investment is becoming important to improve human capital, especially for the poor.

Chapter 3 presents a general literature review on microcredit. The chapter will provide general ideas and concepts of microcredit and microfinance, microcredit providers, reasons why the poor use microcredit, reasons for existence of informal credit providers in developing countries, and interest rates charged by microcredit providers. Other relevant literature on empirical methodologies will be presented in each main chapter for each topic of the thesis.

Chapter 4 examines factors affecting the likelihood of credit participation and credit constraints for the poor households, and use of formal and informal credit. In addition to showing the important determinants of participation in each credit sector, the chapter also investigates how poor households' behaviour in the credit market differs between urban and rural areas.

Chapter 5 reviews credit impact studies and impact measuring methodologies and presents the findings for credit impacts on education and

[16] See at http://www.quan9.hochiminhcity.gov.vn/Office_Infor.asp?Cat=9&ID=192

healthcare expenditure. The chapter mainly employs propensity score matching (PSM) to measure the impacts, and multiple treatment effect estimators to detect unobservable selection bias.

Chapter 6 examines whether the impacts are heterogonous by employing the Quantile Regression. The Seemingly Unrelated Regression (SURE) estimator is also applied to analyze household budget shares of the poor households.

Chapter 7 focuses on the impacts of household credit on child schooling (current enrolment and schooling gap). Probit and Negative binomial models are applied in the chapter. The chapter restricts analysis to a sub-sample of children aged 6 to 18 years old.

Chapter 8 presents the conclusions. The shortcomings of the study are also discussed to provide some further avenues for future research in the field.

APPENDICES

Appendix 1.1: Sample distribution and sampling procedure

Ward name (1)	No of poor households (2)	Contribution to total district poor households (3)	Number of household targeted (4)	Selection rate (5)= (4)/(2)	Reser- -vations (6)= 0.25x(4)	Number of selected household (7)= (4)+(6)
PhuocBinh	314	6.8%	80	0.25	20	100
TNPA	307	6.6%	78	0.25	20	98
LongTruong	467	10.1%	119	0.25	30	149
LongPhuoc	484	10.5%	123	0.25	30	153
Total	1,572	34.0%	400		100	500

Sources: Figures in column 1 are from Statistical Department of District 9 (2007), and Department of Labour, Invalids and Social Affairs of District 9 (2008).

Two-step sampling was used, first selecting wards and then households. First, all 13 wards of the district were partitioned into two groups based on preliminary socio-economic information from the district government statistics report. The first group was more urbanised and highly populated (over 2,800 people/km^2). This group consists of seven wards: Phuoc Binh, Hiep Phu, Phuoc Long A, Phuoc Long B, Tang Nhon Phu A, Tang Nhon Phu B, and Tan Phu). The second group was less urbanised and less populated (below 1,500 people/km^2), and has retained some agricultural economic activities. This group included six wards: Long Truong, Long Thanh My, Long Binh, Long Phuoc, Phu Huu, Truong Thanh). I randomly selected two wards from each group. Accordingly, in the first group Tang Nhon Phu A (TNPA) and Phuoc Binh (PB) were selected, and in the same way, Long Truong (LT) and Long Phuoc (LP) were selected from the second group.

Appendix 1.2: Some basic information of the surveyed wards

Ward name	Population density (persons/km^2)	Contribution to district poor households (%)	Population in agricultural sector 2003 (%)	Population in agricultural sector 2006 (%)
PhuocBinh	18,981	6.8	0.18	0.05
TNPA	6,546	6.6	1.37	0.39
LongTruong	577	10.1	15.34	9.71
LongPhuoc	300	10.5	24.71	17.8
District 9	1,882	34.0	3.67	2.36

Sources: author's estimation from Statistical Department of District 9 (2007).

Appendix 1.3: Economic structure of District 9, Ho Chi Minh City

Sector contribution	2006	
	Value	%
Industrial production (current price)	7,089	65.41
Construction (current price)	439	4.05
Services (current price)	2,870	26.48
Transport (current price)	386	3.57
Agricultural production (current price)	55	0.50
Total	10,839	100

Source: Statistical Department of District (2007)
Note: values in this Table are measured in VND billion; USD/VND=15,965 in 2006.

Figure 1.2: Regional map of Vietnam

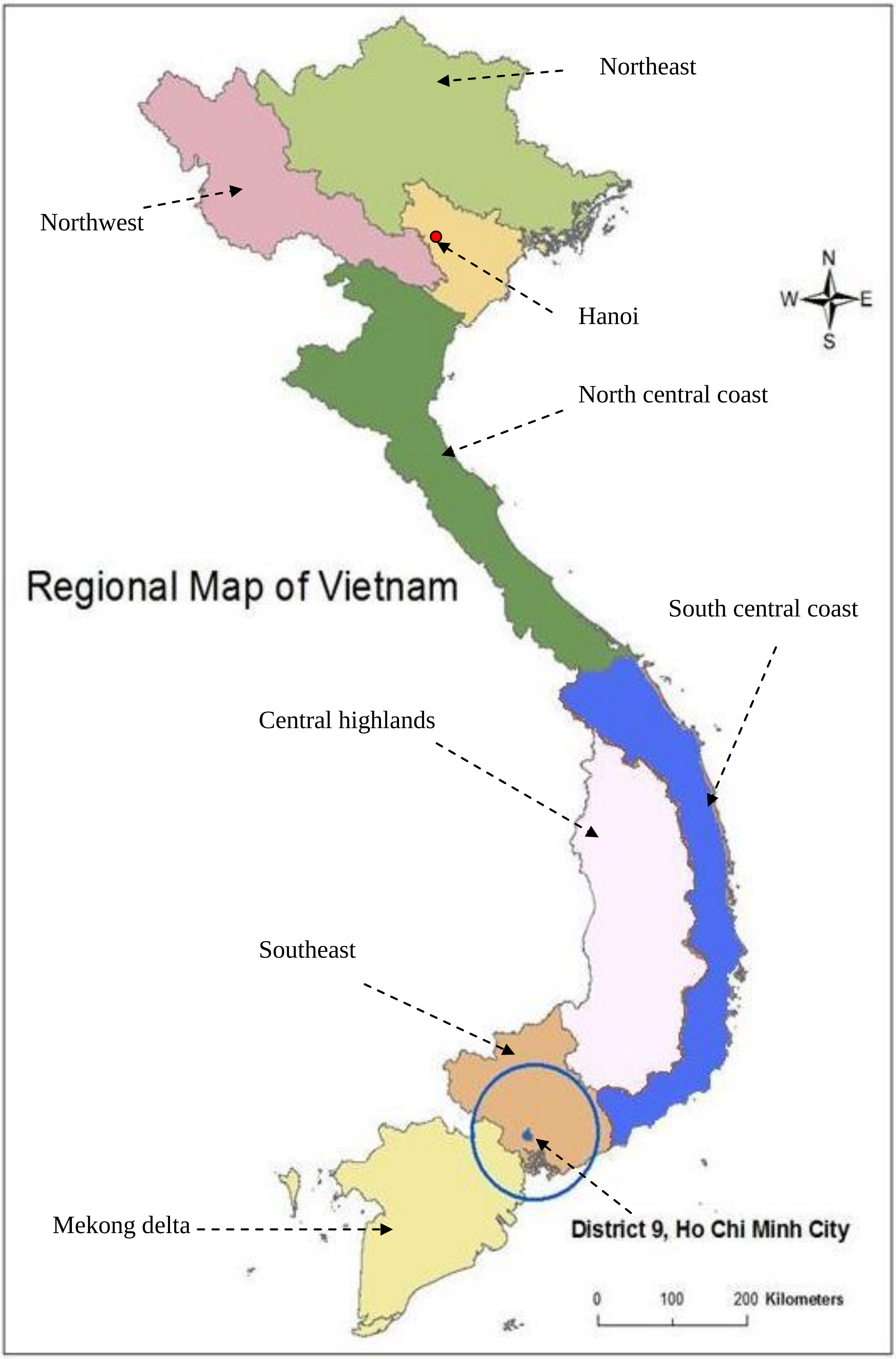
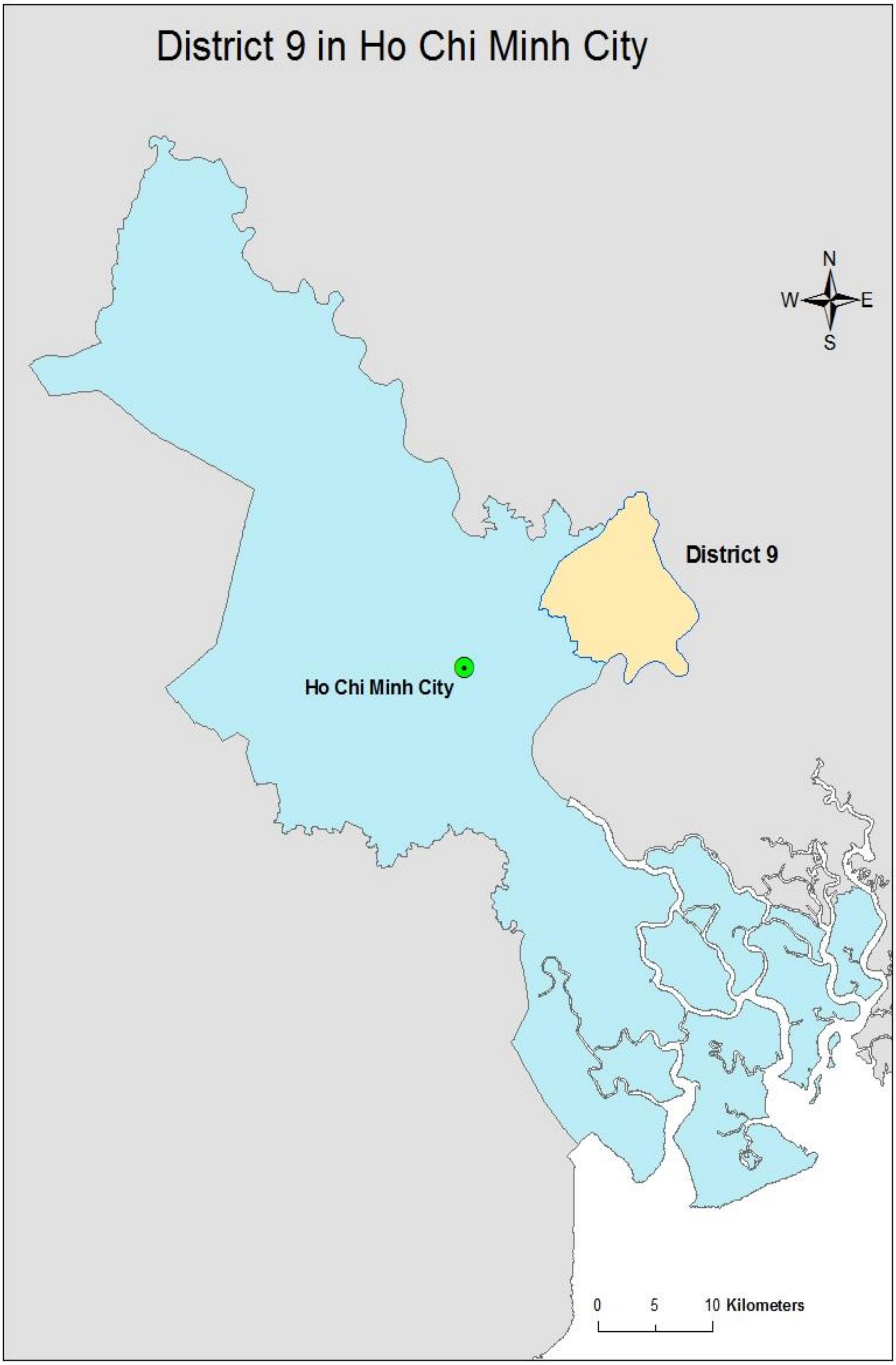


Figure 1.3: Location of District 9 in Ho Chi Minh City



Chapter 2: Background on the increasing importance of education in Vietnam during the economic transition

2.1 Introduction

A key stylized fact about transition economies is that the returns to schooling tend to rise as economic reform progresses (Orazem & Vodopivec, 1995). The increase in returns to schooling in transitional economies are found in the Czech Republic and Slovakia (Chase, 1998), and in Russia, Ukraine, Hungary and Poland (Brainerd, 1998). The rise marks the movement away from distorted labour markets and the effects of longer-term changes in patterns of human capital formation.

Since human capital is the major asset of the urban poor, it is important to study the trend over time in the rate of return to human capital investment. Existing research suggests that Vietnam does not follow the typical pattern (see Appendix 2.2). In 1992, rates of return were very low at the beginning of transition: below 3% using basic Mincerian earnings equation and even below 2% if further controlling for other variables (Glewwe & Patrios, 1998; Gallup, 2002). Using both the basic and extended Mincerian earnings model, Gallup (2002) shows increasing returns between 1992-1998. However, when compared with the world rate of return at about 9% to 10% around the same time (Psacharopoulos, 1994), the rates of return for Vietnam are still low. Contrary to Gallup, estimates reported by Liu (2006) suggest falling rates of returns for men in Vietnam, from 5.9% in 1992 to 3.5% in 1998 and little increase for women, from 4.2% to 4.8% in the same period.[17] One possible reason for the divergence from the patterns in Eastern Europe is that gradual economic reform policies have been applied in Vietnam and the Vietnamese government has intervened in the economy substantially, whilst in Eastern European countries the “Big Bang” reforms were introduced.

To test whether the rate of return to schooling in Vietnam rose during the economic transition, I examine data from the period 1998-2008, called the later period of the reforms, when the reforms may have had longer time to have an

[17] Note that the comparison may be inappropriate because the different models, the Heckman selection correction and OLS model, are applied in 1992 and 1998 respectively by Liu(2006). In the context of Vietnam, higher educated people tend to work in wage-paid jobs, so the selection models typically yield higher returns to schooling (Doan & Gibson, 2009). Given the higher returns by selection models, the decrease in males’ returns over the period from 1992 to 1998 would be smaller; conversely the improvement in female returns would be greater.

effect. Moreover, recent years have seen continued development of the private sector (66% of GDP, and 91% of employment in 2008) which has stimulated competition in the labour market with consequent changes in relative wages. Concurrently, income inequality also rose during the later reform period, with the Gini index rising from 0.35 in 1994 to 0.42 in 2006 (VHLSS, 2004, 2006). Since participation rates in the wage labour market have risen during the period and wage earners have higher education achievement relative to non-wage earners (see Appendix 2.1), the analysis not only relies on the basic Mincerian earnings function but also accounts for sample selection bias.

The next section reviews studies of the returns to schooling in transition economies. Section 2.3 discusses the data and econometric specifications. Section 2.4 presents the results. Section 2.5 discusses possible explanations for the changing returns and provides some conclusions.

2.2 Literature on return to schooling in transitional economies

Existing studies show that rates of return to schooling increase over time in transitional economies. For example, returns to schooling increased from 3.6% in 1988 to 12.2% by 1993 in China, from 1.5% in 1989 to 5.4% by 1994 in Estonia, and from 2.9% in 1986 to 7% by 1996 in Poland (Psacharopoulos & Patrinos, 2004, Table A4). Most of these studies use Ordinary Least Squares (OLS) which does not allow for endogenous schooling choice, but when Heckman and Li (2004) use Instrumental Variables (IV) they find an even higher rate of return to each year of schooling, of around 14% for four-year college attendance in China. This rate is much higher than the rate of return estimated by Chow (2001) for China in the 1980s which was much closer to zero. Johnson and Chow (1997) state that employment in the stationary state sector, which dominated China's urban areas in the late 1980s, leads to lower rates of return. Zhang et al (2005) also suggest that economic reform and technical changes have enhanced competition among workers in China, with the newly-skilled rewarded at an increasing rate. More evidence of the increasing returns during the reforms in transitional economies can be found in Fleisher (2005) and Fleisher, Sabirianova and Wang (2005). These authors find that the speed of economic transition and the degree of economic volatility explain differences in the increase in the rates of return to schooling over time and across economies.

Yet studies of Vietnam for either the single year 1992 or the period of 1992-1998 find low rates of return to schooling, and only a modest rise over time (Gallup, 2002; Glewwe & Patrinos, 1998; Liu, 2006; Moock, Patrinos, & Venkataraman, 2003). It is notable that the study by Liu (2006) was for over ten years of the economic reforms, yet the estimated rate of return was still relatively low (3.5% and 4.8% for male and female in 1998, respectively). However, these studies may not have captured the full effects of the transition to a market-oriented economy given the cautiously gradual nature of early economic reforms in Vietnam. Hence, it is important to see the trend in the returns to schooling over the recent period 1998-2008, which is long enough to allow more apparent effects.

In addition to the timing issue, some existing studies on Vietnam ignored the important problem of sample selection bias (Gallup, 2002; Glewwe & Patrinos, 1998; Moock, Patrinos, & Venkataraman, 2003). Since there was a rising participation rate in the wage labour market during transition, the omission may bias not only the level of the estimated rate of return but also the trend over time. Consequently, in this chapter I control for sample selection bias.

2.3 Model specification

2.3.1 Data

Datasets used in the current chapter are from the 1998, 2002, 2004, 2006, and 2008 rounds of the Vietnam Household Living Standards Survey (VHLSS) conducted by the General Statistics Office of Vietnam (GSO). There are 5,999 households with 28,624 household members in VLSS1998, 29,542 households with 132,374 members in VLSS2002, [18] 9,188 households with 40,419 household members in VLSS2004, 9,189 households with 39,071 members in VLSS2006, and 9,186 households with 38,247 members in VLSS2008. These samples are representative for the national levels of Vietnam. Sub-samples of wage-earners aged from 15 to 60 are used in the estimations, which yield 3,244 from VLSS1998, 26,268 from VLSS2002, 7,177 from VLSS2004, 7,436 from VLSS2006, and 7,532 from VLSS2008.

[18] VHLSS2002 dataset has significantly more observations than other VHLSS datasets. The reason is that Vietnam General Statistical Office (GSO) wanted to provide bigger datasets since VHLSS2002, but the GSO tremendously encountered issues of timing and costs, thus after this survey the GSO maintained the sample sizes at around 9,000 households.

2.3.2 Mincerian earnings model

To estimate the returns to schooling, the Mincerian earnings equation is used:

$$LnY_i = \alpha + \beta_1.S_i + \beta_2 Exp_i + \beta_3 Exp_i^2 + \varepsilon_i \qquad (2.1)$$

where LnY is the natural log of hourly wages including bonuses, allowances, and subsidies (both in cash and in-kind), *S* is years of schooling, *Exp* is potential experience (calculated as age *minus* schooling years *minus* six) and the experience squared term, Exp^2, is included to allow a non-linear pattern in lifecycle earnings. To test increasing rates of return to schooling over time, I use four pooled datasets with the base year of 1998 and the compared-with years, so-called the second year (either 2002 or 2004 or 2006 or 2008) and an interaction term between years of schooling and a year dummy for the compared-with year. In addition, to capture the gender difference in earnings, I also include a dummy variable for gender and its interaction term with the second year dummy. The estimation model now is as follows:

$$LnY_i = \alpha + \delta_0.Year_2 + \beta_1.S_i + \delta_1.S_i{*}Year_2 + \beta_2.Exp_i + \delta_2.Exp_i{*}Year_2 + \beta_3.Exp_i^2$$
$$+ \delta_3.Exp_i^2{*}Year_2 + \beta_4.Gender + \delta_4.Gender{*}Year_2 + \upsilon_i \qquad (2.2)$$

2.3.3 Sample selection bias-corrected model

Sample selection bias results when the subset of wage earners used for the Mincerian earnings function is not randomly sampled from the general population. OLS estimates using the Mincerian earnings equation are biased and not representative for the whole population since the OLS estimates the return to schooling for a subset of wage-earners only. To address the problem I apply the sample selection model (Heckman, 1979) as follows:

Wage equation: $$w_i = z_i \beta_1 + u_{1i} \qquad (2.3)$$

Where w_i is log of hourly wage, z_i is a vector of schooling, experience and gender variables for individual i

Selection equation: $$h_i^* = x_i \beta_2 + u_{2i} \qquad (2.4)$$

where h_i^* is a latent variable; and w_i is observed if $h_i = 1$, and $h_i = 1$ if $h_i^* > 0$, and w_i is not observed if $h_i = 0$, and $h_i = 0$ if $h_i^* \leq 0$. X_i is a vector of schooling, experience, gender, household size and household non-wage income. The selection equation is used to correct the sample selectivity bias. People may self-select into wage employment sector according to their education, household size and non-wage income. Furthermore, the assumptions about the errors are that:

$$u_{1i} \sim NID(0, \sigma^2) \text{ and } u_{2i} \sim N(0,1) \text{ and } cov(u_{1i}, u_{2i}) = \rho_{12}.$$

In the first estimation stage, a binary Probit model on all observations (those in wage employment and those not) is used to estimate the correction term λ_i, which is the inverse Mill's ratio or Heckman's Lambda: $\lambda_i = \phi(x_i \beta_2)/\Phi(x_i\beta_2)$. The term is then included in the second stage of the augmented earnings function:

$$w_i = z_i \beta_1 + \sigma_{12}. \lambda_i + \eta_i \quad (2.5)$$

These two equations can also be estimated in one single step procedure using Heckman maximum likelihood estimator, which is more efficient (StataCorp, 2001) than the two-step procedure. Identification is achieved by including variables (x_i) such as household size and household non-wage income in the selection equation but not in the wage equation. Justification for the use of these variables is that they affect wage employment participation probabilities, through changing the opportunity cost of being in the wage labour force, but an employer is unlikely to pay a different wage rate depending on one's household size or non-labour income. Household size may affect wage employment participation because low productivity and limited arable land in the agricultural sector have led to labour surplus in the sector if households have more members. For example, in 2009, 54% of Vietnam's labour force was in the agricultural sector, but that sector contributed only 17% to Vietnam's GDP (PHC, 2009).[19] Therefore, household size relates to labour surplus and affects wage employment participation. Given the same household size, households with higher non-wage incomes from self-employed, family businesses and farming should have a higher reservation wage and hence may not send their members out to work in the wage employment sector. Therefore, household size and non-wage income are likely to significantly affect the probability of being wage-earners.

2.4 Results

The descriptive statistics show that in 1998 the average educational attainment of wage earners in Vietnam was about 9 years,[20] and 10 years by 2008 (Appendix

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[19] Population and Housing Census 2009 (conducted by Vietnam General Statitiscal Office).
[20] Sample size and sampling strategy of VHLSS2002 is quite different from the remaining surveys so the number of schooling years is slightly lower (see VHLSS, 2002 and 2004: Basic Information

2.1). Non-wage earners' education attainment is lower than that of wage earners in all years. The average hourly wage rate was 2,569 Dong (US$0.187) in 1998 and in nominal terms had risen to 8,854 Dong (US$ 0.537) by 2008.

2.4.1 Basic Mincerian estimates of the returns over time

Table 2.1 contains the basic earnings function estimates. All of the coefficients are statistically significant at the 1% level but the explanatory power of the model is substantially higher in 2008 than in 1998. The coefficient on years of schooling implies an average private rate of return to an additional year of education of 2.9% in 1998 rising to 9.5% by 2008. These results obviously show the increasing returns to schooling during the recent economic reforms. The results are also quite consistent with the increasing trend found in other transition economies. For example, Zhang et al (2005) report a seven percentage point rise in the rate of return to schooling in China between 1988 and 2001.

The female wage is lower than males'. According to the coefficient on the gender dummy variable in the first column of Table 2.1, hourly wages were about 14.8% higher for men than for similar educated and experienced women in 1998; the gap was about 20% in 2008.[21]

2.4.2 Selectivity-corrected estimates of returns to education

To overcome selectivity bias I apply the Heckman selection-correction model. After correcting for sample selection bias, the estimated rates of return to education are somewhat higher than in the OLS estimates reported in Table 2.1. However, the basic feature of a significant rise in the rates of return between 1998 and 2008 is not altered. The full results of using the bias correction model are reported in Table 2.2. The estimated rates of return in most cases rise by about one percentage point relative to the OLS estimates, except in 2002. The rise in the average private rate of return to a year of schooling is illustrated in Figure 2.1 showing both the basic Mincerian earnings equation and selectivity-corrected estimates. Both sets of estimates show a rise of about 6.6 percentage points between 1998 and 2008.

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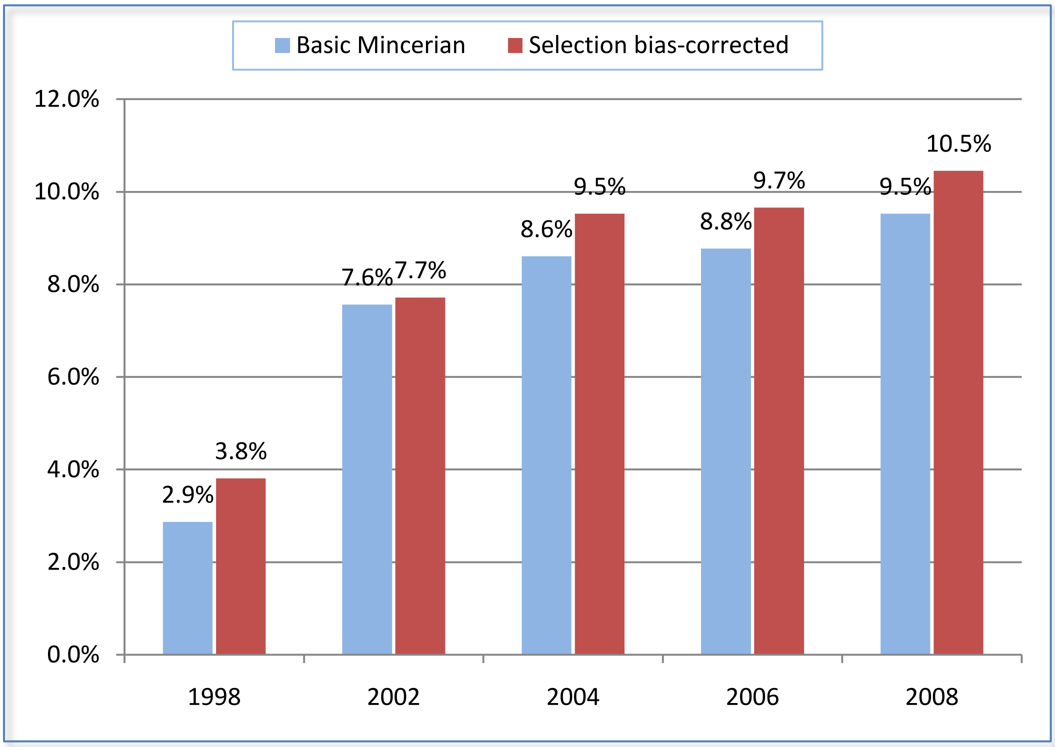
at http://siteresources.worldbank.org/INTLSMS/Resources/3358986-118173055198/3877319-1207074161131/BINFO_VHLSS_02_04

[21] For dummy variables in a semi-logarithmic regression the percentage is calculated as 100 x ($e^{\beta i}$-1)

Figure 2.1: Returns to schooling using cross sectional data sets (Mincerian earnings equation and selection bias-corrected estimates)



The joint estimation of the selection and wage equations shows that the residuals of the two equations are positively correlated for all the years. Specifically, the coefficient on the inverse Mills' ratio (λ) varies from 0.12 to 0.285 and is always highly statistically significant. This implies a positive correlation between the selection equation errors and the wage equation errors, since $\lambda=\rho\sigma$ (and σ must be positive). In other words, individuals with a comparative advantage in entering the wage-earning labour force also earn more than observationally similar workers. Hence the observed wage is higher than the wage that would prevail for a sample of individuals selected at random fashion from the working-age population.

The positive coefficients on years of schooling in the selection equations show a benefit of education which is omitted from the standard wage equations, which is that education provides a higher probability of entering into waged employment. To help interpret the effect, the Probit coefficients from the selection equation are transformed into marginal effects, showing the change in probability of being in waged employment for a unit change in the explanatory variable; I report the marginal effects of characteristics on the probability of waged employment in Table 2.3.

There appears to be a substantial rise over time in the effect of education on the probability of waged employment participation. In 1998, an additional year of schooling raised the probability by just over one percentage point. But ten years later the marginal effect of an extra year of schooling had risen to over three percentage points. In other words, people with higher education have an increasingly higher likelihood of having waged jobs. It is also notable that the overall rise in the predicted probability of waged employment for an individual with average characteristics increased from 14% in 1998 to 34% by 2008. The rapid increase in the probability of being in waged work resulted from the rapid industrialization in Vietnam's urban and peri-urban areas which helped generate more non-farm jobs and absorb surplus labour from rural areas (demand side). Furthermore, the important Enterprise Law (a law for domestic private enterprises) passed in August 1999 (came into effect from 1st January, 2000) stimulated mass establishment of new businesses, especially small businesses which helped absorb surplus labour from the agricultural sector (mostly self-employed family farming) to waged employment sector (industrial and service sectors). The Vietnam enterprise statistics show that the number of enterprises increased substantially, from 42,288 in 2000 to 155,771 by the end of 2007, and 76% were domestic private and limited liability enterprises.[22] These enterprises are the main labour absorbers in Vietnam (Tran & Doan, 2010). This helps to explain the reason behind the rise in the probability of being wage earners over the studied period. The increasing significance of household size as a positive predictor of waged employment is also consistent with the surplus labour interpretation in rural areas (supply side). The opportunity cost of having a household member work in waged employment is lower for a larger family since other family members are able to continue to work either on-farm or in some non-farm informal enterprises. Finally, availability of other non-wage employment from household business, self-employment, and larger farming, which generates household non-wage incomes, reduces the likelihood of being in waged employment.

2.4.3 Checking the robustness of the increasing return to schooling over time

One may question the validity of comparing estimated returns between each year of 2002, 2004, 2006 and 2008 and the base year of 1998 using separate

[22] Available at www.gso.gov.vn/default_en.aspx?tabid=479&idmid=4&itemID=8722

regressions. To validate the comparison and consolidate the finding of rising returns over time, I use pooled data and the interaction terms as discussed in Section 2.3. Specifically, VHLSS1998 is pooled with, one after another, VHLSS2002, VHLSS2004, VHLSS2006, and VHLSS2008 to set up four pooled datasets.

The reason for using the interaction terms is to test whether the returns to schooling are the same over time. The hypothesis is that the slope of the hourly wage, in logarithm (lnY), with respect to years of schooling (S) is the same for both years (1998 and the second year). In other words, I test H^A_0: $\delta_1 = 0$ in the equation 2.2.

The results of the pooled Mincerian earnings equation estimation are presented in Table 2.4. The estimated rates of return to schooling using pooled data 1998/2002, 1998/2004, 1998/2006, and 1998/2008 are presented in columns 1, 2, 3 and 4 of Table 2.4 respectively. In the first column, the return to schooling for year 1998 is 2.9%. For 2002, the rate of returns is 2.87% + 4.69% = 7.6%. Likewise, the rates of return are 8.6%, 8.8% and 9.5% for 2004, 2006 and 2008, respectively (the last row of Table 2.4). The tests for difference in rates of return between the compared-with years and the base year of 1998 are all statistically significant at the 1% level (see the test for H^A_0). Therefore, I can conclude that there is strong evidence against the hypothesis that the returns to schooling are constant over the period. From these estimates, the trend of increasing returns is observed during the period 1998 to 2008. Moreover, the parameter test rejects the hypothesis that all interaction terms jointly equal zero; it implies that the effects of not only education but also other factors on earnings, especially experience, vary over time.

To strengthen the finding, I apply the selection correction model to the pooled datasets, and the estimated results are shown in Table 2.5. In the first stage, the Probit model is applied to estimate the correction term (λ_i). The identification is achieved by including household size and household non-wage income and their interaction terms with the second survey dummies in the selection equation.

The trend of increasing returns is re-confirmed during the period 1998 to 2008 using the selection bias-corrected models with inclusion of the interaction terms. All the differences (δ_1) in rates of return over time are significantly different from zero. The estimates on the interaction terms are all positive and get larger for later years (2002, 2004, 2006 and 2008) showing a clear rising trend of the returns from 1998 to 2008 (Tables 2.4 and 2.5). However, the rate of increase in the rates of return slowed down in the later years from 2004 to 2008. The interaction term coefficients of schooling year and the second survey for pooled 2004/2006 and 2006/2008 data turn out to be insignificantly different from zero.

Overall, the estimated results are robust with a trend of increasing returns to schooling over the studied period in Vietnam. The rate of return seems to match the world rates around 10% (Psacharopoulos, 1994).

The effects of the Asian financial crisis and minimum wages on earnings also appear in the time effect coefficients (δ_0) over time in Table 2.5. Because of the crisis, the Vietnamese government reduced minimum wages in late 1998 (see first column of Table 2.5), and many enterprises also reduced wage rates to keep costs lower in order to survive. During the period 1999-2004, nominal wages were almost kept the same. In other words, because of the wage rate cuts in late 1998, the average wage rate in 2004 is about 10% lower than in 1998. However, due to spontaneous mass strikes in late 2005, the government had to raise minimum wages by 40% in early 2006 (Tran, 2007).[23] The adjustment resulted in a great shift of the time effect (year dummy) in the columns 3, 4, 6 and 7 of Table 2.5.

2.5 Discussions and conclusions

The results reported in the current chapter on returns to schooling in Vietnam using VHLSS1998, 2002, 2004, 2006 and 2008 differ from the previous literature. The rate of return for 2008 is much higher than estimates for either 1992 or 1998 reported by Gallup (2002), Glewwe and Patrios (1998), Liu (2006), and Moock, Patrinos and Venkataraman (2003). Moreover, although there was a rising trend between 1992 and 1998 found by Gallup (2002), or an ambiguous trend examined by Liu (2006), the returns to education for the early economic transition in Vietnam are still relatively low. The current results show a very rapid rise in the rates of return to schooling between 1998 and 2008. The rising trend appears to be

[23] The increase in minimum wages was applied for FDI enterprises. Even the government did not set minimum wages for domestic enterprises, but the labour strikes also happened in domestic enterprises, and therefore the enterprises did increase wages for employees to cool down the labour pressure and to keep employees.

robust to self-selection consideration, e.g. the selection into the waged employment.

What could account for such a rapid rise in the rates of return to schooling, especially given the previously sluggish change reported in the literature? The period studied here coincides with further market opening and integration into the global economy, deeper reforms, and a consequent investment boom with accelerated structural change that has generated many technical-skilled jobs in Vietnam. Investment grew dramatically, from 32% of GDP in 1998 to 41% in 2008, with almost all of the investment into industry and services; about 94% of all investment in 2008. Consequently, the growth rate of the industry sector is very high, about 15.4% during the period 1998-2008 and the industrial growth helped absorb surplus labour from the traditional sector. There was also considerable growth in foreign trade, such that overall openness (the ratio of exports plus imports to GDP) reached over 160% by 2008.[24]

On the labour supply side, changes in labour market laws from the early 1990s were having increasing effects in the early period of the economic reforms. Initial reforms in 1993 to the labour contract system introduced the "basic wage" as the minimum wage. But employers often relied on the basic wage to compute actual wages for employees without concern for appropriate differentials for educational attainment, skills and productivity. Further impetus for negotiating and signing employment contracts came in 1994 when the Labour Code was passed, allowing employers more flexibility in hiring and firing workers. The greater flexibility is also likely to have offered greater mobility for workers, allowing the more highly educated employees to seek out jobs that paid an appropriate wage premium for their skills. On the labour demand side, resulting from the further economic reforms especially the first Enterprise Law issued in late 1999 and a Unified Enterprise Law issued in 2005, investment in industrial production and the service sector was liberalized. A huge increase in the number of enterprises and an investment boom in the industrial and service sector as discussed earlier generated more wage jobs for labourers. Moreover, higher-educated workers may have benefitted from recent technological modernization and the transfer of technical and managerial skills from FDI enterprises which

[24] The information used in the paragraph are available at www.gso.gov.vn/default_en.aspx?tabid=470&idmid=3

resulted from the boom of FDI in the liberalisation period. These are likely causes for increasing returns to schooling over the period 1998-2008.

Moreover, Vietnam joined the WTO in January 2007 with a commitment to further open up markets, including the labour market, so growing competition between employers is likely to continue to affect the returns to schooling in future. Hence, a continued rise in the rate of return to schooling is likely until the country becomes a fully-fledged market economy in common with the pattern observed in other transitional economies. [25]

Chapter summary

This chapter has examined the trend in the rate of return to schooling in Vietnam over the period 1998-2008 when the economic reforms have had a longer time to have an effect. The application of OLS and Heckman selection estimators finds that returns increased quickly during the later period of economic reform but the pace slowed down once rates of return approach the global average of around 10% per year of schooling completed (Psacharopoulos, 1994). The chapter clearly shows that the role of education in earnings has been increasing during the economic transition to a market economy in Vietnam. Therefore, human capital investment is necessary for the poor, who rely heavily upon labour income to escape poverty, especially in urban and peri-urban areas. One of the typical solutions to improve the poor's health and education and to eliminate poverty is providing access to microcredit. In this respect, the following chapters will investigate whether microcredit works for the poor.

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[25] By May 2010, only 22 countries had recognized Vietnam's market economy (Vietnamnet.vn, 28 May 2010).

TABLES

Table 2.1: Basic Mincerian Earning Function Estimates by years (1998-2008)

Variables	1998	2002	2004	2006	2008
Years of schooling	0.0287	0.0756	0.0861	0.0877	0.0952
	(7.64)**	(43.96)**	(37.98)**	(38.99)**	(40.70)**
Experience (years)	0.0150	0.0178	0.0263	0.0299	0.0401
	(2.90)**	(7.43)**	(8.69)**	(10.66)**	(14.05)**
Experience squared	-0.0006	-0.0004	-0.0006	-0.0007	-0.0010
	(3.69)**	(6.19)**	(7.20)**	(8.52)**	(12.31)**
Gender (male=1)	0.1381	0.1614	0.1422	0.1365	0.1820
	(4.55)**	(10.89)**	(7.57)**	(7.68)**	(10.17)**
Constant	0.2935	0.1387	0.1797	0.4060	0.6356
	(6.01)**	(5.80)**	(5.45)**	(12.46)**	(18.66)**
R-squared	0.04	0.15	0.20	0.23	0.26
F-statistics	23.85	550.93	396.45	410.94	466.63
Prob > F (all coeffs=0)	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	3,244	26,268	7,177	7,436	7,532

Robust t-statistics in parentheses (corrected for sampling weights), statistically significant at 10% (+), at 5% (*), and at 1% (**); dependent variable is hourly wage in log, hourly wage is measured in VND 1,000 (and for all Tables hereafter)

Table 2.2: Heckman selection bias-corrected estimates by years (1998-2008)

	1998		2002		2004		2006		2008	
	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection
Years of schooling	0.0381	0.0500	0.0772	0.0386	0.0952	0.0885	0.0966	0.0882	0.1045	0.0874
	(9.24)**	(12.58)**	(42.47)**	(15.65)**	(32.15)**	(27.53)**	(32.60)**	(24.47)**	(33.10)**	(25.51)**
Experience (years)	0.0155	-0.00002	0.0247	0.0810	0.0403	0.0913	0.0436	0.0978	0.0556	0.1037
	(3.00)**	(0.01)	(8.56)**	(39.48)**	(10.75)**	(30.08)**	(12.02)**	(30.82)**	(13.67)**	(33.37)**
Experience squared	-0.0006	-0.0002	-0.0006	-0.0023	-0.0010	-0.0025	-0.0010	-0.0026	-0.0014	-0.0027
	(4.15)**	(2.62)**	(7.50)**	(40.93)**	(9.38)**	(28.98)**	(10.23)**	(30.12)**	(12.44)**	(32.21)**
Gender (male=1)	0.2448	0.4703	0.2018	0.5052	0.2064	0.4557	0.1956	0.4297	0.2433	0.4341
	(7.20)**	(19.57)**	(11.65)**	(35.41)**	(9.52)**	(21.88)**	(9.49)**	(19.75)**	(11.40)**	(20.38)**
Household size		0.0009		0.0446		0.0388		0.0460		0.0444
		(0.12)		(8.19)**		(5.72)**		(5.27)**		(5.83)**
Non- wage income[(a)]		-0.0752		-0.2468		-0.1870		-0.1053		-0.0632
		(7.65)**		(11.01)**		(15.22)**		(9.22)**		(10.34)**
Constant	-0.2649	-1.5129	-0.0542	-1.2933	-0.2240	-1.7260	0.0182	-1.8462	0.2200	-1.8957
	(2.97)**	(23.04)**	(1.08)	(31.85)**	(3.01)**	(31.74)**	(0.24)	(29.01)**	(2.56)*	(32.08)**
Lambda (λ)	0.2849		0.1200		0.2102		0.2049		0.2173	
	(7.49)**		(4.39)**		(6.15)**		(5.92)**		(5.44)**	
Wald χ^2 (4)	143.12		1865.33		1064.76		1110.98		1108.43	
Prob > χ^2 (all coeffs=0)	0.0000		0.0000		0.0000		0.0000		0.0000	
Selectivity test (ρ=0)		χ^2(1)= 56.67**		χ^2(1)= 19.28**		χ^2(1)= 37.59**		χ^2(1)= 34.91**		χ^2(1)= 29.44**
Observations	3,244	20,627	26,268	80,575	7,177	20,866	7,436	21,209	7,5432	21,311

*Robust z statistics in parentheses (corrected for sampling weights); + significant at 10%; * significant at 5%; ** significant at 1%; the dependent variable in wage equation is hourly wage in logarithm and the dependent variable in the selection equation takes value 1 for wage-earners and 0 for non-wage earners.* [(a)] non-wage income divided by 10,000.

Table 2.3: Marginal effects of characteristics on probability of wage employment (1998-2008)

Explanatory variables	1998	2002	2004	2006	2008
Years of schooling	0.0105	0.0133	0.0315	0.0316	0.0316
	(12.23)**	(15.63)**	(27.53)**	(24.68)**	(25.53)**
Experience (years)	0.0001	0.0279	0.0328	0.0353	0.0379
	(0.17)	(39.44)**	(30.07)**	(30.73)**	(33.33)**
Experience squared	-0.0001	-0.0008	-0.0009	-0.0010	-0.0010
	(3.14)**	(40.91)**	(28.99)**	(30.04)**	(32.15)**
Gender (male=1)	0.1028	0.1732	0.1623	0.1549	0.1582
	(18.92)**	(35.41)**	(22.02)**	(19.81)**	(20.51)**
Household size	0.0017	0.0155	0.0154	0.0182	0.0173
	(1.13)	(8.13)**	(6.31)**	(5.52)**	(6.12)**
Non-wage income	-0.0145	-0.0854	-0.0663	-0.0381	-0.0229
(/10,000)	(7.33)**	(10.88)**	(14.62)**	(9.25)**	(10.11)**
Wald χ^2 (6)	698.71	3028.58	1953.72	1699.20	1962.78
Prob > χ^2 (all coeffs=0)	0.0000	0.0000	0.0000	0.0000	0.0000
Prediction of being wage- earners at x-bar	0.14	0.29	0.32	0.33	0.34
Observations	20,836	80,619	20,866	21,209	21,311

Robust z-statistics in parentheses (corrected for sampling weights), statistically significant at 10% (+), 5% (*), and 1% (**)

Table 2.4: Basic Mincerian estimates of returns to schooling with the interaction terms

Explanatory variables	1998/2002	1998/2004	1998/2006	1998/2008	2002/2004	2004/2006	2006/2008
Second year dummy (δ_0)	-0.1548	-0.1139	0.1125	0.3421	0.0410	0.2264	0.2296
	(2.85)**	(1.93)+	(1.92)+	(5.75)**	(1.01)	(4.88)**	(4.87)**
Years of schooling (β_1)	0.0287	0.0287	0.0287	0.0287	0.0756	0.0861	0.0877
	(7.64)**	(7.64)**	(7.64)**	(7.64)**	(43.96)**	(37.98)**	(38.99)**
Schooling years*second year (δ_1)	0.0469	0.0573	0.0590	0.0665	0.0104	0.0017	0.0075
	(11.34)**	(13.05)**	(13.46)**	(15.01)**	(3.67)**	(0.52)	(2.31)*
Experience (β_2)	0.0150	0.0150	0.0150	0.0150	0.0178	0.0263	0.0299
	(2.90)**	(2.90)**	(2.90)**	(2.90)**	(7.43)**	(8.69)**	(10.66)**
Experience*second year (δ_2)	0.0028	0.0114	0.0150	0.0251	0.0085	0.0036	0.0102
	(0.49)	(1.90)+	(2.55)*	(4.27)**	(2.21)*	(0.87)	(2.54)*
Experience squared (β_3)	-0.0006	-0.0006	-0.0006	-0.0006	-0.0004	-0.0006	-0.0007
	(3.69)**	(3.69)**	(3.69)**	(3.69)**	(6.19)**	(7.20)**	(8.52)**
Experience squared*second year (δ_3)	0.0001	-0.0001	-0.0001	-0.0004	-0.0002	-0.0001	-0.0003
	(0.88)	(0.33)	(0.69)	(2.36)*	(1.87)+	(0.51)	(2.56)*
Gender (Male=1) (β_4)	0.1381	0.1381	0.1381	0.1381	0.1614	0.1422	0.1365
	(4.55)**	(4.55)**	(4.55)**	(4.55)**	(10.89)**	(7.57)**	(7.68)**
Gender*second year (δ_4)	0.0233	0.0041	-0.0015	0.0439	-0.0192	-0.0056	0.0455
	(0.69)	(0.12)	(0.04)	(1.25)	(0.80)	(0.22)	(1.80)+
Constant	0.2935	0.2935	0.2935	0.2935	0.1387	0.1797	0.4060
	(6.02)**	(6.01)**	(6.01)**	(6.01)**	(5.80)**	(5.45)**	(12.46)**
Observations	29,512	10,421	10,680	10,776	33,445	14,613	14,968
R-squared	0.14	0.18	0.36	0.50	0.17	0.24	0.30
F-statistics	305.05	337.60	497.49	854.75	494.09	408.52	517.26
Prob > F (all coeffs = 0)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Test (Prob > F) H^A_0: $\delta_1 = 0$	0.000	0.000	0.000	0.000	0.000	0.602	0.021
Test (Prob > F) H^B_0: $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$	0.000	0.000	0.000	0.000	0.001	0.000	0.000
Rate of return for the 2nd year ($\beta_1 + \delta_1$)	*7.56%*	*8.60%*	*8.77%*	*9.52%*	*8.60%*	*8.77%*	*9.52%*

*Robust t statistics in parentheses (corrected for sampling weights); + significant at 10%; * at 5%; and ** at 1%; the dependent variable is hourly wage in log.*

Table 2.5: Heckman selection model for earnings equation with the interaction terms

Explanatory variables	1998/2002		1998/2004		1998/2006		1998/2008		2002/2004		2004/2006		2006/2008	
	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection
Second year	-0.0995	0.2247	-0.1046	-0.2133	0.1243	-0.3349	0.3510	-0.3831	-0.0004	-0.4425	0.2319	-0.1215	0.2444	-0.0504
dummy	(1.81)+	(2.91)**	(1.76)+	(2.51)*	(2.10)*	(3.63)**	(5.84)**	(4.33)**	(0.01)	(6.48)**	(4.84)**	(1.45)	(4.91)**	(0.58)
Years of	0.0339	0.0499	0.0362	0.0500	0.0346	0.0501	0.0349	0.0501	0.0773	0.0386	0.0950	0.0888	0.0943	0.0882
schooling	(8.67)**	(12.57)**	(9.13)**	(12.58)**	(8.84)**	(12.58)**	(8.86)**	(12.58)**	(42.75)**	(15.65)**	(35.06)**	(27.52)**	(34.67)**	(24.52)**
Schooling years	0.0437	-0.0114	0.0597	0.0382	0.0608	0.0378	0.0683	0.0370	0.0145	0.0496	0.0016	-0.0006	0.0057	-0.0007
*second year	(10.35)**	(2.44)*	(13.06)**	(7.48)**	(13.43)**	(7.07)**	(14.89)**	(7.06)**	(4.85)**	(12.26)**	(0.47)	(0.13)	(1.63)	(0.14)
Experience	0.0152	0.0000	0.0154	-0.0000	0.0153	-0.0000	0.0153	-0.0000	0.0254	0.0810	0.0400	0.0914	0.0444	0.0978
	(2.97)**	(0.01)	(2.99)**	(0.00)	(2.97)**	(0.00)	(2.98)**	(0.00)	(9.16)**	(39.49)**	(11.15)**	(30.07)**	(13.30)**	(30.83)**
Experience	0.0116	0.0809	0.0259	0.0912	0.0264	0.0977	0.0381	0.1036	0.0097	0.0103	0.0036	0.0064	0.0105	0.0060
*second year	(1.98)*	(19.90)**	(4.18)**	(19.66)**	(4.39)**	(20.64)**	(6.20)**	(22.10)**	(2.49)*	(2.82)**	(0.87)	(1.45)	(2.54)*	(1.35)
Experience	-0.0006	-0.0002	-0.0006	-0.0002	-0.0006	-0.0002	-0.0006	-0.0002	-0.0006	-0.0023	-0.0010	-0.0025	-0.0011	-0.0026
squared	(3.95)**	(2.64)**	(4.06)**	(2.63)**	(3.98)**	(2.63)**	(3.99)**	(2.63)**	(8.07)**	(40.94)**	(9.77)**	(28.97)**	(11.32)**	(30.12)**
Exp_squared	-0.0001	-0.0020	-0.0004	-0.0022	-0.0004	-0.0024	-0.0007	-0.0025	-0.0002	-0.0002	-0.0001	-0.0002	-0.0003	-0.0001
*second year	(0.44)	(19.22)**	(2.28)*	(17.96)**	(2.27)*	(19.07)**	(4.04)**	(20.09)**	(2.05)*	(1.88)+	(0.52)	(1.38)	(2.47)*	(0.72)
Gender	0.1966	0.4697	0.2224	0.4702	0.2042	0.4704	0.2080	0.4704	0.2059	0.5052	0.2050	0.4560	0.1978	0.4296
(male=1)	(6.14)**	(19.53)**	(6.87)**	(19.56)**	(6.41)**	(19.55)**	(6.44)**	(19.55)**	(12.31)**	(35.40)**	(9.79)**	(21.92)**	(10.02)**	(19.75)**
Gender	0.0174	0.0353	-0.0116	-0.0149	-0.0169	-0.0404	0.0266	-0.0360	-0.0235	-0.0485	-0.0092	-0.0263	0.0460	0.0046
second year	(0.51)	(1.26)	(0.32)	(0.47)	(0.48)	(1.25)	(0.75)	(1.12)	(0.98)	(1.93)+	(0.35)	(0.87)	(1.78)+	(0.15)
Household size		0.0017		0.0012		0.0013		0.0012		0.0445		0.0384		0.0459
		(0.24)		(0.17)		(0.18)		(0.17)		(8.20)**		(5.81)**		(5.24)**
HHsize* second year		0.0427		0.0381		0.0461		0.0442		-0.0033		0.0077		-0.0014
		(4.79)**		(3.94)**		(4.06)**		(4.26)**		(0.39)		(0.70)		(0.12)
Non_wageincome		-0.0748		-0.0754		-0.0757		-0.0758		-0.2466		-0.1875		-0.1051
		(7.54)**		(7.62)**		(7.62)**		(7.63)**		(11.03)**		(15.68)**		(9.19)**

(Continued next page)

Table 2.5: Heckman selection model for earnings equation with the interaction terms (continued)

Explanatory variables	1998/2002		1998/2004		1998/2006		1998/2008		2002/2004		2004/2006		2006/2008	
	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection	Wage	Selection
Non_wage income *second year		-0.1713 (6.96)**		-0.1106 (7.05)**		-0.0299 (1.97)*		0.0124 (1.06)		0.0596 (2.34)*		0.0823 (4.99)**		0.0418 (3.25)**
Constant	-0.0127 (0.19)	-1.5178 (23.07)**	-0.1478 (2.12)*	-1.5143 (23.01)**	-0.0529 (0.80)	-1.5145 (22.96)**	-0.0726 (1.03)	-1.5142 (22.96)**	-0.0738 (1.63)	-1.2933 (31.90)**	-0.2151 (3.34)**	-1.7248 (31.71)**	0.0229 (0.38)	-1.8458 (28.95)**
Lambda (λ)	0.1560 (6.33)**		0.2250 (8.85)**		0.1766 (7.82)**		0.1866 (7.16)**		0.1322 (5.60)**		0.2055 (7.24)**		0.2116 (7.96)**	
Wald χ^2	2075.12		1990.36		2889.50		4369.98		3462.52		2448.51		3277.96	
Prob > χ^2 (all coeffs=0)	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	
Selectivity test (ρ=0) $\chi^2(1)$		39.81**		75.21**		60.03**		50.76**		31.36**		52.21**		62.98**
Observations	29,512	101,202	10,421	41,493	10,680	41,836	10,776	41,938	33,445	101,441	14,613	42075	14,968	42,520

*Robust z statistics in parentheses (corrected for sampling weights); + significant at 10%; * significant at 5%; ** significant at 1%*

APPENDICES

Appendix 2.1: Means and standard deviations (in parentheses) of some main variables of wage earner sub-sample

Variables	1998	2002	2004	2006	2008
Hourly wage rate	2.569 (2.399)	3.781 (5.534)	4.442 (4.155)	5.777 (5.266)	8.854 (9.109)
Years of schooling	9.180 (3.833)	8.216 (4.308)	9.779 (3.841)	9.854 (3.839)	10.044 (3.850)
Experience (years)	15.224 (10.397)	16.487 (10.348)	16.469 (10.603)	16.613 (11.075)	16.921 (11.306)
Age (years)	31.581 (10.777)	32.845 (10.538)	33.489 (10.886)	33.853 (11.145)	34.398 (11.289)
Non-wage earners' schooling years	7.965 (3.474)	7.443 (3.572)	8.484 (2.923)	8.658 (2.935)	8.852 (2.943)
No of wage earners[(a)]	3,244	26,268	7,177	7,436	7,532
Fraction[(b)] of wage earners (aged 15-60)	15.3%	32.8%	35.2%	35.5%	36.4%

Sources: VHLSS1998, 2002, 2004, 2006, and 2008. Hourly wage rates are in 1,000 Vietnam Dong, and in 1998 the average exchange rate was 13,765 Dong/USD, 15,244 Dong/USD in 2002, 15,705 Dong/USD in 2004, and 15,965 in 2006, 16,481Dong/USD in 2008. [(a)]Excluding some extreme outliers; [(b)]Observation probability after Probit for the selection equation.

Appendix 2.2: Existing studies on rates of returns to schooling in Vietnam for 1992-1998

Author(s)	Year	Coefficient	Method	Other controlled variables
Glewwe & Patrinos (1998)	1992/93	0.016	OLS	Experience, experience squared, gender, types of school, regions
Gallup (2002)	1992/93 1998	0.029 0.050	OLS	Experience, experience squared
	1992/93 1998	0.019 0.035	OLS	Experience, experience squared, gender, minority, Chinese, non-agricultural employment, private, employer, HCMC, Hanoi
Moock et al, (2003)	1992/93	0.048	OLS	Experience, experience squared, log week hours worked
Liu (2006)	1992/93	Male: 0.059 Female: 0.042	Heckman selection	Experience, experience squared, married, migrant, urban, regions, majority, state employees, SOEs employees, industries
	1998	Male: 0.035 Female: 0.048	OLS	

Chapter 3: Literature review on microcredit

In this chapter, the general literature on microcredit, microfinance and credit to the poor is reviewed. Specific literature relevant to the methodologies used will be presented in subsequent chapters, in turn, for each topic of the thesis. In contrast, this chapter reviews general concepts of microcredit and microfinance, reasons why the poor need microcredit, reasons for existence of informal credit in developing countries, and also discusses interest rates charged by microcredit providers.

3.1 Microcredit and microfinance

The concept of credit is not new. The history of microcredit and microfinance can be summarized as follows (see Helms, 2006, p. 2-5). Small, informal savings and credit groups were documented in 1462 in Europe, but until 1700s small loans were first lent to poor farmers who had no collateral. After the Second World War, especially during the 1950s-1970s, many countries established state-owned development banks, credit institutions and credit cooperatives to provide loans to small farmers in hopes of improving agricultural productivity and incomes. In this period, because of heavily subsidized credit and state intervention, most of the credit programs failed.

In early 1970s, experimental programs which provide small loans to the poor were initiated in Bangladesh, Brazil, India, and in few other countries, marking the birth of microcredit. In the 1980s, microcredit programs proved and asserted that the poor are reliable clients and willing to pay cost-recovered interest rates (Helms, 2006, p. 4). Due to the success of microcredit institutions like ASA, Grameen Bank in Bangladesh and Bank Rakyat in Indonesia in reaching the poor, remaining profitable and providing growth opportunities in the long term, the 1990s witnessed the blossoming of microfinance institutions (MFIs) in many countries and massive attention from development researchers, international development agencies and networks. As a result, microcredit was considered an approach to eliminate poverty. Since then, the term microfinance, instead of microcredit, has been widely used (Helms, 2006, p. 5). The event of Nobel Peace Prize awarded to Muhammad Yunus and his Grameen Bank from Bangladesh in 2006 benchmarked the roles of microcredit and microfinance in improving living standards for the poor and low-income households, and its position in the financial system.

Today, the term microcredit has been interchangeably used with microfinance. According to Robinson (2001, 2004), microcredit is defined as the extension of small loans to the unemployed, poor entrepreneurs, and poor households who usually lack collateral or fail to meet minimum requirements for access to traditional formal credit. Yunus further extended the term microcredit to "loans from agricultural credit, or rural credit, or cooperative credit, or credit unions, or from moneylenders" (Yunus, 2006, p. 1). Meanwhile, microfinance is a broader concept; it is defined as small-scale financial services to the poor and low-income households, which include consumer credit, loans, savings, pensions, insurance, remittances services and other basic financial services.[26&27]

Microfinance not only provides loans to poor households to generate income and smooth consumption but more importantly to help poor households to diversify their income sources, increase their financial confidence, and to manage their economic production more efficiently (Robinson, 2001). Thus, microfinance has been widely considered an innovative tool to help the poor and the poorest not only to generate employment and income but also to come out of poverty (Robinson, 2001). Today, microfinance has become a part of the financial market where formal and informal credit institutions extend small loans to the poor. The borders between microfinance and formal financial system have become blurred (Helms, 2006, p. 5). Microfinance is considered as a segment of the broader financial market where microfinance is the "lower end" or grassroots level of the broader financial system and not an isolated marginal sector (Nieto, 2007). For the formal financial institutions, microfinance or microcredit is simply an extension of small-amount-loans to the poor, low-income households, small entrepreneurs, the unemployed, farmers, or small traders. Today, the formal financial institutions increasingly move down to the "lower end" to serve large numbers of poorer, disadvantageous and remote clients since these clients practically also bring profits to them (Helms, 2006).

3.2 Microcredit providers

According to a microfinance handbook by Ledgerwood (1999), credit providers can be divided into three sectors: Formal, semi-formal and informal institutions. Formal credit providers are regulated by official laws and general regulations as well as specific regulations by central banks. They include commercial banks, development banks, agricultural banks, social policy banks, postal saving funds and non-bank institutions. Semi-formal credit providers are registered officially, based on corresponding laws and regulations including commercial laws, but are not regulated and controlled by central banks. They include credit and saving associations, credit funds, credit cooperatives, multiple-purpose cooperatives, NGOs and registered self-help groups. Finally, informal

[26] http://www.cgap.org/p/site/c/about/
[27] http://www.cgap.org/p/site/c/template.rc/1.26.1302/

credit providers are not regulated by any banking laws and regulations. They include moneylenders, pawn-brokers, Rotating Savings and Credit Associations (ROSCAs), relatives, friends, neighbours, small traders and unofficial self-help groups/community groups.

Both semi-formal and informal credit providers often provide small loans and have quite similar operational principles (e.g. collateral-free, working within a geographical proximity), so they sometimes can be classified as informal credit sector so as to contrast with formal credit sector. The role of formal credit is often to finance large scale projects of firms, while the role of informal credit is to finance micro projects of low-income households or the poor (Bouman, 1989). Clients of informal credit are often unbankable households, written off by commercial banks because of illiteracy (low ability to repay as the banks presume) and insufficient collateral (Armemdariz & Morduch, 2010). Although informal credit providers are sometimes regarded as exploiters of the poor due to the high interest rates they charge, they do exist throughout human history (Pain, 2008, p. 49). They always complement formal credit, especially for the poor, and provide credit and other financial services to most poor households (Helms, 2006, p. 37).

About 80 percent of the 4.5 billion people living in developing countries are unable to have access to formal financial services, and in many countries most of the poor have little or no access to credit sources (Robinson, 2001, p. 11). Therefore, the poor have to seek substitute sources of credit from informal providers (Amin, 1989; Rutherford, 1999; Srinivas, 1991). This reliance on informal credit providers reflects several facts (Robinson, 2001, p. 186-187): *First*, informal credit usually offers short-term and small loans which are matched with the demands of the poor. *Second*, loans are immediately available when needed, in a flexible manner with minimum documentation or even without any complicated paper requirements or collateral. *Third*, the informal credit, such as ROSCAs, also creates opportunities for the poor to save and to earn interests for their savings, while the formal credit institutions often ignore small savings.

However, the informal credit has some *controversial* disadvantages: the *first* is high interest rates. For example, in many countries, informal credit providers charge from 10% to 100% per month (Robinson, 2001, p. 16). However, not all informal credit providers charge high interest rates; loans from neighbours, relatives, friends and mutual-help groups have low interest rates or even are interest-free. Interest rates charged by informal interest-earned lenders vary widely, and the degree of exploitation (high interest rates) in informal credit markets declines with economic development in the operating areas (Robinson, 2001). For example, in some countries like Thailand, Pakistan, Bangladesh and Bolivia, moneylenders (a typical type of informal credit provider) charge quite low interest rates, while the lenders charge very high rates in other countries such as the Philippines, Indonesia, Nicaragua and Malawi (Robinson, 2001, p. 199-200). *Second*, informal credit providers are often able to provide limited amounts and for short time frames, often less than one year (Robinson, 2001, p. 187), that are not suitable for long term and big projects. But for household level projects, there is little evidence that informal funds are scarce and rejections are due to other reasons rather than availability of funds (Aleem, 1993, Siamwalla et al, 1993). *Third*, the lenders usually keep accounts in traditional ways and issue no legal receipts or documents which may lead to a failure to provide evidence when disputes arise. That is why informal credit activities such as ROSCAs, private money-lending, etc. are illegal in many countries (Robinson, 2001, p. 188). However, the lenders often work within small geographical areas, have good information about their borrowers or know borrowers' reputation, and have interlinks (between lenders and borrowers) and these factors enable them to successfully collect their loans.

3.3 Microcredit interest rates

Microcredit interest rates are typically higher than conventional credit rates, especially for informal sources like moneylenders, pawnbrokers, ROSCAs, etc. For example, a recent survey of 13 developing countries showed that informal credit lending rates are commonly between 40% and 80% per annum (Banerjee & Duflo, 2007, 2010), and from 10% to 100% per month in many other countries, (Robinson, 2001, p. 16). Even big microfinance institutions (MFIs) such as Grameen Bank charges 20% per annum, and other MFIs in Asia and the Pacific usually charge 30% to 70% per annum (CGAP, 2002).

The key principle of running any financial business including microfinance is that, for long run viability, revenue should cover all administration costs, costs of capital, risk, and increasing equity (CGAP, 2002). Only sustainable institutions are able to provide permanent access to their resources to hundreds of millions of clients, and they are therefore forced to charge higher effective-interest rates to cover all the costs and earn reasonable profits to survive in the long term (CGAP, 1996; Morduch, 2000). In practice, the poor that are excluded from formal credit providers due to insufficient collateral would be well served by the sustainable microfinance institutions (Morduch, 2000).

On the other hand, only microcredit institutions that receive preferable sources or subsidies from governments and donors are able to offer low-interest-rate loans. However, these generally benefit only a small number of borrowers for a short period (CGAP, 2002). Subsidized loans have low repayment and high default rates in many countries such as Vietnam, India and China (Robinson, 2001) because the borrowers think that their loans are 'gifts' so that there is no motivation to repay. There is an argument that only MFIs that stand on their feet without subsidies from governments and donors and follow the "win-win" proposition are able to serve more poor clients; these MFIs therefore have to charge high interest rates in order to cover the costs and earn some reasonable profit (Morduch, 2000).

Other reasons for microcredit providers to charge higher rates than conventional banks are: Costs of paperwork to make a small loan are not significantly different from larger loans; this leads to higher costs charged on each unit amount of small loans than costs for the larger loans (Morduch, 2000). In addition, poor clients often live in backward (geographical/physical or socially isolated) areas where infrastructure, such as road systems and telecommunication facilities, is poor. Thus, transaction costs are higher due to difficulties in administering, loan monitoring and the travel required by credit lenders to reach borrowers' places (Morduch, 2000; CGAP, 2002). This makes lending costly and riskier. Moreover, clients often have no collateral, low education, and lack legal documentation so that they are likely to be deemed greater risk (Armendariz & Morduch, 2010; Morduch, 2000). Consequently, the rates should be high enough to offset the higher likelihood of credit default.

On the demand side, poor borrowers can accept higher rates of interest because they earn a higher rate of return to additional unit of capital borrowed relative to richer households because of decreasing returns to capital. Armendariz and Morduch (2005, 2010) argue that the poor entrepreneurs have a higher marginal return on capital and thus higher ability to repay than the richer entrepreneurs. However, very high interest rates applied by moneylenders and pawnbrokers do not necessarily reflect higher returns on capital, they may reflect the urgent need for money and riskier loans. Borrowers have no option other than 'hot' or 'urgent' loans to survive today, although they may suffer serious destitution tomorrow. On the other hand, running businesses requires many things more than capital; skills, other inputs, market information, social networks, etc, of which the richer likely have more than the poor. In this case, the poorer borrowers may have lower marginal returns than richer borrowers; thus, risk-adjusted interest rates for the poorer clients may be lower than for the richer (Armendariz & Morduch, 2005, 2010; Morduch, 2000; Weiss & Montgomery, 2005). Furthermore, there may be "insider" factor blocking capital flows from lower demand locations (low interest rate) to high demand locations (Klonner & Rai, 2010). These are likely causes for interest rate differences between the microcredit (informal) credit markets and the traditional (formal) credit markets. Thus, the interest disparity always exists. In other words, the interest rate differences between credit markets for the rich and the poor do not create the capital flows between them.

Nevertheless, Fernando (2006) states that we should not consider microcredit interest rates too high by comparing microcredit interest rates with that of commercial banks because such comparisons are inappropriate because the poor sometimes have to pay extra money to access formal (subsidized) sources due to credit rationing and rent-seeking practices by credit officers. If these costs are added, real interest rates of the loans may be much higher, and the comparison therefore may be misleading.

In some developing countries like Vietnam, to avoid high interest rates the government has set up interest rate ceilings and introduced massive subsidies on interest rates. The consequence of this policy is that there has been a shortage in credit supply, and the outreach has been low for lenders (Morduch, 2000). To reach a targeted number of poor customers, governments have to add on to interest rate shortfall or provide preferred credit funding to credit lenders. As a result, the subsidized institutions have heavily relied on subsidies and government fund sources to keep their operations going. For instance, the Vietnam Bank for Social Policies (VBSP) in 2005 received about USD55.38 million of subsidies for interest disparity and transaction costs, accounting for 51.2% of total revenue of the bank. An increasing reliance on subsidies has been evident over time, from 32% of total bank revenue in 2003, to 44% in 2004 and 51.2% in 2005.[28] This means that self-sufficiency of the bank is about 50%, and the bank has had a very high rate of losses at 13.7% (i.e. return on equity is -13.7%) and the profit margin at -97.6% in 2006.[29] Therefore, subsidies to microcredit institutions result in inefficiency in terms of operating costs per borrower, and subsidy level is strongly correlated with lower profit rates (Cull, Kunt, & Morduch, 2009, p. 14).

Interest rate ceilings may improve the affordability of financial sources for the poor; however, interest rate ceilings may lead to losses to microcredit providers if they are without subsidies from sponsors (NGOs or governments), since the regulated rates are not high enough to cover all costs of the loans. This will undermine viability of microcredit institutes in the medium and long term. Furthermore, according to Fernando

[28] Annual Report of VBSP, available at http://www.vbsp.org.vn/Icon_BCTN/36.gif
[29] Microfinance – The MIX market – profile for VBSP available at www.mixmarket.org/en/demand/demand.show.profile.asp?ett=2156

(2006, p. 5), interest rate ceilings cause a shift to more short-term loans to avoid risks such as high inflation. In addition, interest rate ceilings create an excess demand for credit, and thus result in credit rationing and rent-seeking/bribe opportunities for credit officers (p. 4). Finally, interest rate ceilings, if without subsidies, force the microcredit providers to lower their mobilisation or saving interest rates in order to survive, and the lower saving interest rates in turn will discourage the poor from saving (Morduch, 2000). Interest ceilings suppress the poor's savings and are not the answer to improve access to financial services for the poor (Fernando, 2006).

Governments' intervention like subsidisation and interest ceilings are associated with inefficiency; subsidized credit programs have failed globally (Morduch, 2000). They have led to high default rates, government budget deficit, undermining savings mobilisation, mis-targeting to richer and politically-connected entrepreneurs, and eventually high costs for targeted clients (p. 620). Especially, government interventions in subsidised credit programs have diverted cheap credit sources far away from targeted poor households but have brought the cheap loans to politically powerful groups of non-poor households. This is evident in many countries such as Thailand, Vietnam and China (Coleman, 1999, 2006; Morduch, Park, & Wang, 1997; Nguyen, 2008). Thus, minimizing roles of government, especially direct involvement, is necessary to improve the transparency and accountability of programs and guarantee properly credit allocation to targeted poor and low-income households (Morduch, 2000).

3.4 Microcredit clients

Clients of microfinance in developing countries are the unbankable (Armemdariz & Morduch, 2010; Helms, 2006). They include self-employed, micro-enterprise owners, small farmers, street vendors, shopkeepers, small traders at marketplaces, and factory workers.

The poor can be classified as (see Helms, 2006): Destitute, extreme poor, moderate poor and vulnerable non-poor depending on their positions relative to the poverty line (a common poverty line is set at US$1/day/person). Accordingly, the destitute are at the bottom 10% of all the poor; from 10% to 50% are the extreme poor; the top 50% of households below the poverty line are called the moderate poor, and those who are just above the poverty line are classified as vulnerable non-poor. Not everyone under the poverty line is a microcredit client; most microcredit clients are the moderate poor and vulnerable non-poor, those are around the poverty line, while the destitute group or the poorest is almost excluded (Helms, 2006, p. 21). This is observed in many countries such as Bangladesh, Philippines, Bolivia and Uganda. The destitute group are not potential clients of microcredit institutes, even of formal microcredit sources that are subsidised by governments or by international organisations. Since the likelihood of repayment of those clients is very low, the destitute group needs direct assistance rather than credit e.g. immediate income transfer or allowances.

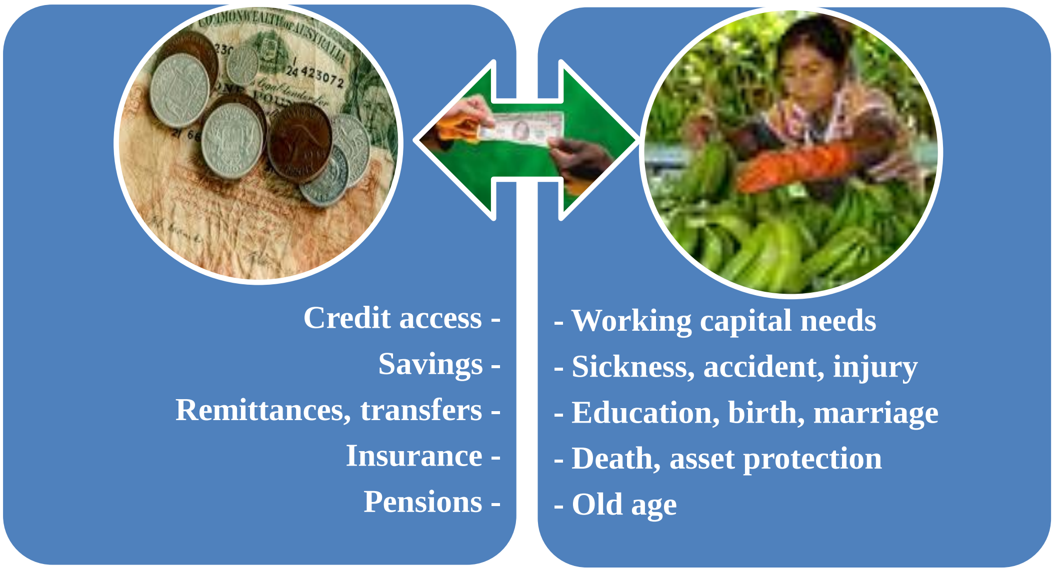
In Bangladesh, where the mass-microcredit programs, such as ASA, BRAC, BRDB and Grameen Bank, are more independent from government intervention and less subsidised, it is likely that the microfinance programs reached eligible clients, the poor (Amin, Rai, & Topa, 2003; Armendariz & Morduch, 2005; Morduch, 2000). On the other hand, subsidised microcredit programs have mis-targeted the eligible clients, and ended up in the hands of non-poor clients because subsidies and credit allocation have been influenced by politically powerful groups (Morduch, 2000, p. 624). For example, in Vietnam, the non-poor account for a larger proportion of the program participants (Nguyen, 2008); in Northeast Thailand microfinance programs failed to target the poor, and instead the richer households benefited from the programs (Coleman, 2006). Eliminating subsidies may avoid the mis-targeting problem (Morduch, 2000). With market-level interest rates, the non-poor will not be interested in the program loans anymore since they will not earn an interest-disparity that is the key drive for them to borrow from the subsidized programs. In addition, at market interest rate levels, the non-poor will not borrow from the programs as the program loans are often small so that they do not match the non-poor’s bigger demand.

3.5 The roles of microfinance for the poor and low-income households

In the essay “*The poor and their money”,* Rutherford (1999) shows that the poor use their money for three main purposes: life-cycle events, emergency needs, and income generation or investment. The life-cycle events include birth, marriage, funerals, holidays, and school fees. Emergency needs include healthcare expenditure (sickness, injury), labour loss, employment loss, property loss, and disasters. The investment involves family businesess, farming, buying land, buying household, production assets and inputs.

According to Helms (2006), to sucessfully help the poor out of poverty, programs or policies need to enable the poor to have permenant access to credit and to have facilities or capacity to reduce risks. Thus, the poor need more than credit, financial services such as savings, money transfers, pension fund, and insurance are also needed. These financial services and credit will ensure stable and continuous cash flows for the poor currently and in future. To illustrate how the microfinance services help the poor in different circustances, the diagram below can shows the relationships between the poor and microfinance service providers. On the left hand side are the financial (microfinance) services that the poor need, on the right hand side are events/occurences or shocks that induce demand for the microfinance services.

Credit and other financial services help the poor expand business, diversify income, promote education and health, save for future, make use of financial services, and consequently reduce poverty and improve future livelihoods for the poor (Helms, 2006; Littlefield et al, 2003; Robinson, 2001).



Source: The photos used in this diagram are from http://www.uncorneredmarket.com/photos/tag/microfinance/page1/

Many current studies show that microfinance has a positive impact on the poor (Littlefield et al, 2003; Pitt & Khandker, 1998; Nguyen, 2008), while other studies such as Banerjee, Duflo, Glennerster and Kinnan (2009), Coleman (1999, 2006), Morduch (1998), Roodman and Morduch (2009), Roodman (2009), and Rosenberg (2010) find limited evidence of the impacts. But Helms (2006) is optimistic about impacts of microfinance; she said "existing evidence on the impact of microfinance probably underestimates the value of financial services for the poor, because studies focus only on microcredit" (p. 32). Microfinance helps the poor not only to survive but also to plan for future, improve living condition, invest in healthcare and education, and to empower women (Helms, 2006; Littlefield et al, 2003). However, microcredit is not expected to work for everyone, especially for the destitute and hungry, nor work everywhere (Armendariz & Morduch, 2010; Helms, 2006).

3.6 Conclusions

Although in many developing economies there has been great progresses in economic development over the last 30 years, millions of the poor and low-income households, who are just around the poverty line, rely heavily upon microcredit, especially informal credit, as primary sources of credit to meet their demand for credit. The existence of an informal credit sector in almost all of the economies around the world especially in developing countries is the reality and reflects the failure of formal financial markets to meet poor clients' financial needs. Understanding the determinants of access to informal credit and its impacts compared with the impacts of formal credit is thus an important topic, which the rest of this thesis addresses.

Chapter 4: What determines credit participation and credit constraints of the poor in peri-urban areas

4.1 Introduction

Microfinance, including microcredit as the main part, and other micro financial services such as insurance and savings vehicles, has become a popular tool in poverty alleviation efforts in developing countries (Armendariz & Morduch, 2010; Microcredit Summit, 2004). The poor have inadequate access to formal credit resources because of barriers imposed by lenders and relatively high transaction costs for small-size loans that discourage lending to the poor (e.g. Khandker, 2005; Pitt & Khandker, 1998; Microcredit Summit, 2007). Thus, a sizeable proportion of poor households are almost certain to borrow from the informal credit sector (Banerjee & Duflo, 2007, 2010). In Vietnam, the poor typically fail to meet the formal credit requirements, and hence find it difficult to access formal credit. Recent studies show that in 2002 the informal credit sector provided approximately 50% of the total credit to the poor and low income households (IFC, 2006; VDR,[30] 2004).

The success of microcredit in alleviating poverty first depends on credit participation and credit constraints. The existing empirical evidence on determinants of credit participation and credit constraints is well established for rural areas (Barslund & Tarp, 2007; Diagne, 1999; Diagne, Zeller, & Sharma, 2000; Izumida & Pham, 2002; Nguyen, 2007; Thaicharoen, Ariyapruchya, & Chucherd, 2004), and for western countries (Avai & Toth, 2001; Chen & Chivakul, 2008; Crook, 2001; Crook & Hochguertel, 2005; Crook & Hochguertel, 2007; Del-Rio & Young, 2005; Margi, 2002). In contrast, investigation into determinants of credit participation and credit constraints for peri-urban households, in Vietnam and elsewhere, is rare.

Lack of analysis for peri-urban areas probably results from a belief that in these areas financial services are available to everyone. This may not be true, as the poor in developing countries who migrate to cities often dwell in peri-urban areas and usually rely on credit to smooth their consumption expenditure.[31] Unlike the rural poor who can increase labour earnings via off-farm work, reduce purchased other inputs and use more self-produced products when they face shocks, the urban or peri-urban poor cannot have the same coping strategies (Kochar, 1995). Most of the urban and peri-urban poor are

[30] Vietnam Development Report

[31] For example, data from HCMC Statistical Office show that population growth rates are 2.7% and 82% for urban districts and peri-urban districts over the last 12 years (1997-2009), respectively. These data are available at
http://www.pso.hochiminhcity.gov.vn/so_lieu_ktxh/2000/Dan_so_va_lao_dong/0203.htm/view, and
http://www.pso.hochiminhcity.gov.vn/so_lieu_ktxh/2009/Dan_so_va_lao_dong/0201.htm/view

unskilled and involved in the informal sector; most of them tend to work casually as wage or daily workers (Rashid, 2000, p. 247). During adverse (e.g. disaster, economic) shocks, work opportunities and wages reduce, so households are unable to offset the income decline by sending more members to labour markets or by increasing the number of working hours (Fallon & Lucas, 2002; McKenzie, 2004; Rashid, 2000). Therefore, to fill the income shortage, credit would become important in these areas, especially for the poor who have low savings (Skoufias, 2003). Nevertheless, the determinants of credit participation and credit constraints for the poor in these areas remain unknown.

This gap in the current literature prompts the current study to search for answers to the following questions: *First*, does the presence of financial institutions fully offer the peri-urban poor access to credit resources? *Second*, what are determinants of credit constraints and credit participation by the poor? *Third*, is the credit market segmented, even just amongst the poor, in the peri-urban areas?

The chapter is structured as follows: the next section provides theoretical background. Section 4.3 discusses the analysis framework. Empirical results are presented in Section 4.4. The final section offers a summary.

4.2 Theoretical background

Although the concept of credit access and participation has been used interchangeably in the literature, access to credit differs from credit participation. Access to credit means a household is both able to borrow, thanks to credit availability, and can satisfy lending criteria, including interest rate levels, established by lenders; regardless of whether they borrow or not. On the other hand, credit participation means that a household has chosen to borrow and has already borrowed, even the borrowed amounts may be at the market clearance point (or optimal point) or any points below the below the market clearance point if without interest subsidies. A household that has participated in borrowing activities has, of course, access to particular credit resources, whereas a household having access to credit may choose whether or not to participate in borrowing activities.

According to Diagne (1999, p. 7), credit participation is more related to potential borrowers' choice (demand-side), whereas credit access is more from the supply-side and related to potential lenders' choice. Therefore, the concept of credit access closely links to credit constraints. Full credit access implies no constraints imposed by lenders. Likewise, limited credit access means some forms of credit constraints being imposed. As a result, to examine factors determining demand for credit should model credit participation, while factors determining credit supply should be components of credit constraints if credit resources are unlimited.

There are two approaches to investigate household credit participation and credit constraints: the demand for consumption smoothing and the analysis of determining factors. The first approach has been widely used to examine how smooth household consumption is during adverse income shocks, and the ways by which households can cope with risks. Although the current research does not have data to test the consumption smoothing theory, the consumption smoothing approach helps to explain why households need credit and why households are credit constrained. Once we learned why households need credit transaction and why household are credit constrained, the second approach is employed to determine factors affecting household credit participation and constraints. I shall discuss these approaches in turn.

4.2.1 Consumption smoothing approach

In the *consumption smoothing* approach, there are two ways to explain the existence of credit transactions: the permanent income hypothesis and community risk pooling/sharing.

First, the permanent income hypothesis: according to Friedman (1957), any change in consumption caused by shocks to income (transitory income) could be smoothed sufficiently by borrowing under perfect capital markets,[32] because households will try to maximize their utility over the life cycle by borrowing when having transitory low income and by saving when having transitory high income. Thus, demand for household credit is derived from the demand for smoothing consumption against the income shocks. The violation of assumptions of perfect capital markets in developing countries where the financial markets are heavily distorted by asymmetric information problems, however, could be a reason to justify the existence of credit constraints and credit rationing (Conning & Udry, 2007; Morduch, 1995). Therefore, under imperfect financial markets, consumption is not completely smoothed (Dercon & Krishnan, & Studiën, 2000; Duflo & Udry, 2004; Goldstein, 2004). Dependence of consumption on not only permanent income but also transitory income implies that households are not able to borrow sufficiently to fill the income gap caused by adverse shocks; thus, under this condition the households are credit-constrained (Morduch, 1995, p. 107).

[32] The theory says that both household income and consumption consists of permanent and transitory components; while permanent components of income and consumption are positively related, there is no correlation between transitory components or between either transitory component and the permanent component of the other variable. Therefore, a temporary change in income (i.e. transitory income) would have no effect on consumption.

However, the violation of the permanent income hypothesis could result from not only credit constraints but also household precautionary behaviour (Deaton, 1991; Morduch, 1990; Paxson, 1992). Household savings, other accumulated assets, external assistance and remittances or cash transfers could be effective absorbers of the income shocks which help to keep household consumption smoothed even if the household is credit-constrained (Deaton, 1991; Kurosaki, 2006). In such cases, demand for credit would not be derived directly from demand for consumption smoothing, and the credit constraints could not necessarily be inferred from tests for consumption smoothing.

Moreover, many households, especially the poor, may not have enough savings. Such households may want to spend money today rather than waiting until tomorrow; and this approach to spending makes credit constraints more persistent (Armendariz & Morduch, 2005, p. 193). And of course, no savings means no accumulated assets. Armendariz and Morduch argue that credit constraints may be explained by the existence of saving constraints.

In addition, in many developing countries, a significant proportion of the population is not insured or is inadequately insured. Many governments are not able to afford safety nets for their citizens to help them mitigate adverse shocks. Therefore, adverse health shocks to non-working members of households, which do not directly affect household income, will still generate credit demand if the households have inadequate savings to pay healthcare bills (Kochar, 1995). Consequently, credit constraints may occur if the households are not able to borrow sufficiently.

In addition, in developing countries the demand for credit is not only for coping with income shortage, but also for financing household economic activities; under imperfect financial markets, the credit constraints may exist if the households are not able to borrow adequately to meet the demand for production capital. The credit demand would be greater if households either have larger production projects or face adverse shocks to their production activities such as animal death, harvest loss, drought, flooding, and other disasters; hence households need more capital to enlarge or restore their production.

The community relationship and risk pooling/sharing: is another channel of adverse shock absorption and risk sharing. To see how changes in current income affect household consumption, and how completely a community shares the risks, we consider the following equation (Townsend, 1995, p. 90).

$$\frac{\ln c_t^i - \ln c_\tau^i}{t-\tau} = \beta\left(\frac{\overline{\ln c_t^g} - \overline{\ln c_\tau^g}}{t-\tau}\right) + \phi\left(\frac{\ln y_t^i - \ln y_\tau^i}{t-\tau}\right) + \xi_{t,\tau}^{i,g} \tag{4.1}$$

where y^i and c^i are income and consumption of household i respectively, g is the group (village or community), and ζ is the error term. The dependent variable is the consumption change for a particular household. The main explanatory variables of equation (4.1) are: the first component is mean consumption change for the community or risk-pooling group, and the second component is the idiosyncratic income change for a particular household, and the last is any other shocks. If the risk sharing (pooling) is complete, the coefficient of group consumption will be one (β=1), and the coefficient of idiosyncratic household income will be zero (ϕ=0).

Empirically, β is often smaller than one and ϕ is greater than zero; it implies the risk sharing is substantial, but less than perfect (Townsend, 1995, Table 2). This fact rejects the hypothesis of full risk-sharing because ϕ is greater than zero. The higher ϕ is the less complete is insurance by risk-pooling community/group; changes in household consumption are more associated with changes in current household income. For instance, Townsend (1995, p. 93-94) shows that the coefficient of risk-sharing is lower for the greater Bangkok region than for other poorer regions in Thailand because the consumption changes of the households in Bangkok are highly correlated with their own idiosyncratic income shocks, but less correlated with pooling of risk among their community. On the other hand, households in rural (poorer) areas have better risk-sharing than their counterparts in urban areas since the changes in village's average consumption affects household's consumption through borrowing transactions and other mutual help (Townsend, 1994).

Furthermore, Townsend (1994) finds that household consumption co-moves with village average consumption, but is not much influenced by current household income, sickness, unemployment, and other household idiosyncratic shocks. He also finds that responses to changes in income in order to smooth consumption could be borrowing activities from the community or banks. Moreover, responses to household income fluctuations are credit transactions rather than sales of assets (Lim & Townsend, 1994; Townsend, 1994).

Kochar (1995, 1999) argues that income shocks do not necessarily require credit participation because households are able to prevent the decline of household income by increasing labour earnings and reducing other inputs. On the other hand, income fluctuations caused by demographic shocks (e.g. death, sickness) can only be smoothed by using credit and depleting non-financial assets since households have lost potential earning labour. Kurosaki (2006, p. 75) provides evidence that villagers in Pakistan used credit, especially informal credit, as the most important mechanism to cope with adverse income shocks.

Furthermore, the demand for insurance and credit is high in most low-income economies (Morduch, 1995, p. 105) because income is not only low but also unstable. Households become vulnerable when consumption declines after adverse income shocks. In well-functioning markets, households may not be vulnerable to income shocks because all risks should be diversified away, hence idiosyncratic or transitory shocks should have no impact on consumption. Households can borrow or save to fill up or send off the changes in their income, therefore, consumption smoothing is complete. When credit markets are imperfect, households are constrained in their ability to obtain credit, and the effect of transitory income on consumption would help explain unsmoothed consumption.

In short, the response to consumption fluctuations is complex. It can be community risk sharing, production diversification, labour earnings, external assistance, sales of accumulated assets, and borrowing. Labour income may be one of the solutions, but it is ineffective in conditions of inadequate employment (both wage and self-employment) during economic downturn/crises (McKenzie, 2004); credit access is the other absorber of the shocks. However, capital market imperfection may result in imperfect risk sharing and credit constraints.

4.2.2 Analysis of determining factors approach

This approach to investigating credit participation and credit constraints uses household information, such as physical and human capital endowments, in a reduced-form regression equation, to identify the determinants of credit participation and constraints (Barslund & Tarp, 2007; Chen & Chivakul, 2008; Crook & Hochguertel, 2005, 2007; Diagne, Zeller & Sharma, 2000; Jappelli, 1990; Zeller, 1994). Most of the studies define credit-constrained households as the rejected applicants and discouraged households. Kedir, Ibrahim, and Torres (2007) add another group of households; those who are lent an amount less than the amount they demanded (borrower’s optimum amount). However, few of the studies define precisely the credit-unconstrained households. They implicitly treat all households who did not borrow as credit-constrained; but in fact, some households did not borrow because they had enough resources. These households should be considered credit-unconstrained.

Credit participation (demand-side factors) should be determined by borrowers' demand for credit and their creditworthiness, which is used as criteria to sort out clients by the lenders. Therefore, factors determining credit participation should represent either borrowers' demand for credit or borrowers' creditworthiness. If borrowers are from the general population rather than just from poor households, better endowments (physical and human resources - components of creditworthiness) may enable the households to participate in borrowing activities (Johnston & Morduch, 2007). For example, income, farm size, land and house value, other durable and fixed assets, education, household size or labour force, occupation and ages are important determinants of credit participation (Crook, 2001; Del-Rio & Young, 2005; Diagne, 1999; Izumida & Pham, 2002; Margi, 2002; Nguyen, 2007).

On the other hand, if focusing on poor households, the above determinants may play other roles in explaining credit participation. They could be driving demand factors rather than components of creditworthiness. For example, physical endowments (e.g. assets/land) and human endowments (e.g. education) have a negative relationship with credit participation (Khandker, 2001; Khandker, 2005; Thaicharoen, Ariyapruchya, & Chucherd, 2004).

The different determinants of credit participation for different groups of borrowers imply that the credit markets in developing countries are segmented. The lenders may apply different strategies to screen applications and evaluate clients' creditworthiness for different credit segments (Conning & Udry, 2005, p. 7).

Credit constraint (supply-side factors) is the typical feature of the credit market in developing countries (Conning & Udry, 2005). Potential borrowers are often excluded, discouraged, rejected, or rationed to smaller loans relative to what they might have optimally demanded. Potential borrowers are systematically sorted out due to their low endowments.

Determinants of credit constraints would better represent barriers to credit markets than those of credit participation because credit constraints reflect obstacles on the credit supply side that block borrowers from accessing credit sources. Thus, the factors affecting credit constraints are components of lending criteria, and are often used by the lenders to evaluate their clients' creditworthiness in order to sort out potential borrowers. Factors such as age, income, assets, education, occupation, and borrowing experience are empirically found to be significant determinants of credit constraints (Avai & Toth, 2001; Chen & Chivakul, 2008; Crook & Hochguertel, 2005, 2007; Kedir et al, 2007; Jappelli, 1990; Zeller, 1994).

In addition, in many poor countries, especially in rural areas where real estate markets are rigid due to asymmetric information problems and difficulties in enforcing contracts (Morduch, 1995), the fixed assets are often under-valued. As a result, fixed assets such as land and dwellings may not be important determinants of credit constraints and credit rationing. For example, Zeller (1994) shows that physical collateral plays an insignificant role in credit rationing in both informal and formal credit markets. Even in urbanised areas, where the real estate markets function better, lack of legal documents for household property would also cause lenders to not accept the pledge of the fixed assets as collateral or else they substantially undervalue the assets when they are lodged as collateral.

Another obstacle to borrowing involves invisible barriers such as complicated or ambiguous procedures. These discourage potential borrowers, especially the poor, who are likely to have little education and limited social networks. Further, many households "fear" commercial banks and civil servants when they deal with them to have documentation completed for borrowing from formal credit suppliers. Consequently, poorer households may treat the banks and civil servants as alien entities, so the close geographical proximity fails to help the urban poor access formal credit. For example, Barslund and Tarp (2007) find that in Vietnam distance to nearest banks has no effect on credit rationing. It is likely that nearby households are not impeded by the distance to the banks, but are probably blocked by the invisible obstacle of complicated procedures. Therefore, improving education and simplifying lending procedures may be necessary to mitigate credit constraints.

4.3 Analytical framework[33]

4.3.1 Models for the probability of credit participation and credit constraints

In this study, the aim is to determine possible factors affecting credit participation and credit constraints. Credit participation and credit constraints are binary variables where participating in credit (or being credit-constrained) takes a value of one, and zero otherwise. Thus, to estimate the probability of credit participation and credit constraints when dependent variable Y equals one given a set of explanatory variables x_i, the Probit model is employed. The Probit model is written as follows.

$$p(Y=1|\, x_{1,}\, x_{2,\, \ldots,}x_k)= \Phi(z)= \Phi(\beta_0+ \beta_1.x_1 + \beta_2.x_2 + \ldots+\beta_\kappa x_k)$$

where p_j is the outcome of the dummy (0-1) variable for the *j*th observation, Φ is the standard cumulative normal, x_j is the vector of explanatory variables for observation *j*

[33] Sample design and data collection were discussed in Section 1.7 of Chapter 1.

and β is the vector of coefficients to be estimated. The Probit coefficients are not directly interpretable, but marginal effects for continuous variables could be calculated (at the mean) as:

$$\left.\frac{\partial \Phi(\mathbf{x}\beta)}{\partial x_k}\right|_{\mathbf{x}=\bar{\mathbf{x}}} = \phi(\bar{\mathbf{x}}\beta)\beta_k$$

where x_k is a vector of independent variable (k is the number of independent variables), β is the vector of estimated coefficients, and ϕ is the normal density function. For dummy variables, the discrete change in probability when the dummy variable switches from zero to one is calculated as $\Phi(\bar{\mathbf{x}}_1\beta) - \Phi(\bar{\mathbf{x}}_0\beta)$ where $\bar{\mathbf{x}}_1 = \bar{\mathbf{x}}_0 = \bar{\mathbf{x}}$ except that the *i*th elements of $\bar{\mathbf{x}}_1$ and $\bar{\mathbf{x}}_0$ are set to one and zero respectively (StataCorp, 1997).

The current literature suggests using physical and human capital endowment as explanatory variables to predict the probability of credit participation and credit constraints. Therefore, the Probit models include the household head's gender, age, education, marital status, household size,[34] pre-survey income per capita,[35] pre-survey assets (land/house/durable assets),[36] a dummy variable for phone ownership,[37] location dummies, and distance to nearest bank.[38] Effects of other borrowing neighbours may affect the probability of credit participation and constraints because neighbouring households are likely to share information and borrowing experiences. So the proportion of borrowing neighbours within a radius of one kilometre of each respondent is used as a proxy for information flows.[39] Accordingly, the model for credit participation is as follows:

$$BORROWER_{ij} = \beta_0 + X_{1ij}\,\beta_1 + X_{2ij}\,\beta_2 + X_{3j}\,\beta_3 + \varepsilon_{ij} \qquad (4.2)$$

where $BORROWER_{ij}$ is a binary variable representing whether household i in ward j borrowed (1) or not (0). X_{1ij} is a vector of household characteristics and X_{2ij} is the

[34] The number of under-18-year old children and number of older-than-60-year old members are collinear with household size. However, the ratios of various age groups to total household size may not collinear with household size, thus I ran a regression with ratio of children to household size and ratio of the older-than 60 years old members to household size, but the estimates are statistically insignificant. As a result, I dropped the variables.

[35] The income was collected by the District 9 Department of Labour, Invalids and Social Affairs in collaboration with the Hunger Elimination and Poverty Reduction Unit of each ward in the district from December 2005 to January 2006 in order to classify poor households who are eligible for receiving assistance including preferred loans from the HEPRF.

[36] I use only assets acquired over 24 months prior to my survey (rather than all assets) and pre-survey income (rather than current expenditure) to avoid possible endogeneity and reverse causality.

[37] I use the dummy as a proxy for information access; I do not classify phones as durable assets because recently phones, especially landline phones, are given free by the service suppliers. Subscribers have to pay connection fees, monthly fixed charge and actual call charges.

[38] To avoid the collinearity between ward dummy and the distance, the interactions between the distance and ward dummy are used instead of the distance itself.

[39] Alternatively, borrowing neighbours may cause a crowding-out effect because they could be potential competitors when credit resources are limited.

physical endowment of household i in ward j, while X_3 is a vector of ward-level characteristics. These include the proportion of borrowing households within a radius of one kilometre and the distance to the nearest bank within a ward.

In equation (4.2), all borrowers are treated the same in the sense that there is no difference between those who borrowed from formal credit sources and those who borrowed from informal credit suppliers. However, it is possible that segmented markets may exist causing the determinants of who can borrow from formal credit to be distinct from the determinants of who can access only informal credit. As a result, multinomial models may help to uncover the roles of each factor in segmented credit markets. Accordingly, the model can be as follows:

$$SPECIFIED\_BORROWER_{ij} = \beta_0 + X_{1ij}\,\beta_1 + X_{2ij}\,\beta_2 + X_{3j}\,\beta_3 + \varepsilon_{ij} \qquad (4.3)$$

where $SPECIFIED\_BORROWER_{ij}$ is a multinomial variable representing whether a household i in ward j did not borrow (N), or borrowed from the informal credit only (I), or from both the informal and formal credit (B), or from the formal credit only (F). X_is are the same as previously defined.

The results of equation (4.3) are reported as the Relative Risk Ratios (RRR). For example, for binary independent variables, suppose beta (β) is for the head's gender (1, 0 for male and female respectively), then to get the RRR:

$$e^{\beta_1} = \frac{\frac{P(Y=Y_1)}{P(Y=Y_0)}\,|\,X=1}{\frac{P(Y=Y_1)}{P(Y=Y_0)}\,|\,X=0} \qquad e^{\beta_2} = \frac{\frac{P(Y=Y_2)}{P(Y=Y_0)}\,|\,X=1}{\frac{P(Y=Y_2)}{P(Y=Y_0)}\,|\,X=0} \qquad e^{\beta_3} = \frac{\frac{P(Y=Y_3)}{P(Y=Y_0)}\,|\,X=1}{\frac{P(Y=Y_3)}{P(Y=Y_0)}\,|\,X=0}$$

where $e^{\beta 1}$, $e^{\beta 2}$, and $e^{\beta 3}$ is RRR of household head's gender of corresponding outcome Y_1, Y_2, and Y_3.

For a continuous variable (e.g. head's age),[40] the RRR (or e^{β}) is obtained as follows:

$$e^{\beta_1} = \frac{\frac{P(Y=Y_1)}{P(Y=Y_0)}\,|\,X+1}{\frac{P(Y=Y_1)}{P(Y=Y_0)}\,|\,X} \qquad e^{\beta_2} = \frac{\frac{P(Y=Y_2)}{P(Y=Y_0)}\,|\,X+1}{\frac{P(Y=Y_2)}{P(Y=Y_0)}\,|\,X} \qquad e^{\beta_3} = \frac{\frac{P(Y=Y_3)}{P(Y=Y_0)}\,|\,X+1}{\frac{P(Y=Y_3)}{P(Y=Y_0)}\,|\,X}$$

To examine the determinants of credit constraints, the following model is used:

$$CONSTRAINT_{ij} = \alpha_0 + X_{1ij}\,\alpha_1 + X_{2ij}\,\alpha_2 + X_{3j}\,\alpha_3 + \upsilon_{ij} \qquad (4.4)$$

[40] If continuous variables in log form, we now are measuring the marginal increase in the RRR ratios for 100% increase in X at the mean.

where $CONSTRAINT_{ij}$ is a binary variable representing whether household i in ward j is credit-constrained (1) or not (0). Credit-constrained households include rejected households, discouraged households, and partial borrowers; credit-unconstrained households consist of full borrowers and other households who do not want to borrow because they have sufficient resources to meet their demand for credit. X_is are the same as defined in credit participation modelling.

4.3.2 Tobit Type 2 model for credit amount received

Regarding credit amounts received, the dependent variable is continuous and can vary between zero (for non-borrowers) and a certain positive value. Therefore, in this case the Tobit model provides an appropriate estimator (Verbeek, 2004).

Let Y* denote credit amount borrowed, and Z_i is vector of explanatory variables, the estimation equation is postulated as follows:

$$Y_i^* = \beta.Z_i + u_i \qquad u_i \sim NID(0, \sigma^2)$$

However, for a large number of households the credit amount is zero; Tobin (1958) suggests the following model:

$$Y_i = \begin{cases} \beta.Z_i + u_i & \text{if} \quad Y_i^* > 0 \quad \text{for households with credit amount is positive, and} \\ 0 & \text{if} \quad Y_i^* \leq 0 \quad \text{for households with credit amount is zero} \end{cases}$$

A shortcoming of standard Tobit model regression is that the model may produce biased and inconsistent estimates if heteroscedasticity exists (Amemiya, 1984; Johnston & Dinardo, 1997, p. 441). To overcome the problem, a Tobit Type 2 model, which can account for heteroscedasticity, is used. The model is implemented by using the interval regression estimator, which is a generalisation of the Tobit model, where responses can be point data, interval data, left-censored or right-censored. The error terms of the regression are presumed to be normally distributed, and the log likelihood function is as follows:

$$L = -\frac{1}{2}\sum_{j \in C} w_j \left[\left(\frac{y_j - x\beta}{\sigma} \right)^2 + \log 2\pi\sigma^2 \right] + \sum_{j \in L} w_j \log \Phi\left(\frac{y_{Lj} - x\beta}{\sigma} \right)$$
$$+ \sum_{j \in R} w_j \log\left[1 - \Phi\left(\frac{y_{Rj} - x\beta}{\sigma} \right) \right] + \sum_{j \in I} w_j \log\left[\Phi\left(\frac{y_{2j} - x\beta}{\sigma} \right) - \Phi\left(\frac{y_{1j} - x\beta}{\sigma} \right) \right]$$

where $\Phi(\ )$ is the standard cumulative normal and w_j is the sampling weight for the jth observation. The vector of parameters of interest, β plus σ, are chosen to maximize the likelihood by a modified Newton-Raphson routine. For $j \in L$ the data are left-censored, where the unobserved y_j is only known to be less than or equal to the threshold y_{Lj}. For $j \in R$ the data are right-censored, with the unobserved y_j only known to be greater than or equal to the threshold y_{Rj}. The other $j \in I$ observations are intervals, where all that is known is that the unobserved y_j is in the interval $[y_{1j}, y_{2j}]$. In the current case, the data of credit amounts received are left-censored, the unobserved y_i is known to be equal to zero for non-borrowing.

4.4 Empirical results

4.4.1 Main features of poor households' credit

As a preview to the econometric results, a general overview of poor households' credit in the peri-urban study areas of HCMC is provided. Formal credit provides 55% of credit (Table 4.1), which is mainly credit resources from government subsidised sources such as Vietnam Bank for Social Policy (VBSP), social political organisations, the Job Creation Support Fund (JCSF) and the Hunger Elimination and Poverty Reduction Fund (HEPRF). These lenders provide 'preferred' or sometimes called 'soft' or 'subsidised' loans (low interest rate and easy lending conditions), and are the main sources of credit accounting for 51% of the total loans to the poor in the peri-urban areas (Table 4.2).

However, the informal credit sector still plays a substantial role in providing credit to the poor; approximately 45% of loans, albeit of a smaller average value than formal loans. Amongst informal credit providers, mutual help amongst relatives, friends and neighbours provide more than one third of all loans. The Rotating Saving and Credit Associations (ROSCAs), private moneylenders and pawnbrokers only provide 8.4% of total loans to the poor (Table 4.2). This low share may be because interpersonal trust and social ties are weak in peri-urban and urban areas (Allcott et al, 2007; Debertin, n.d; Hofferth & Iceland, 1998).

Interest rates for the poor's loans vary widely, from 0.78% per month on average for the formal credit to 2.14% (about 26% per year) for the informal sector with a large standard deviation of 5.9% (Table 4.2). The interest rate for informal credit is high compared to formal credit, but still lower than in many other developing countries. For example, a survey of 13 developing countries by Banerjee and Duflo (2007, 2010) shows that informal credit lenders charged annual rates of 40% to 80% per annum. However, when loans from friends, relative and neighbours that are almost interest-free are excluded, the informal lenders charge very high interest rates at 11.3% per month or about 130% per year, higher than in many other developing countries. According to another survey by Conning and Udry (2005, p. 8), informal credit lenders charge interest at 40% to 120% annually in Pakistan, 20% to 120 % in India, 24% to 84% in rural Thailand, and over 90% annually in Nigeria.

Table 4.3 shows that the main purpose of the loans taken by the poor in the peri-urban areas is for non-production (73.4%). Consumption expenditure such as food, school fees and healthcare accounts for about 64% of total loans. On the other hand, only a quarter (in terms of both number of loans and loan value) is used for small production and businesses. This usage pattern is similar to the pattern found by Kedir et al (2007) in urban Ethiopia, but is much different from typical loan usage patterns in rural areas (Barslund & Tarp, 2007; Johnson & Morduch, 2007).

Table 4.4 shows the incidence of credit participation and credit constraints. Less than 10% of households had sufficient capital and did not want to borrow. Another 10% were discouraged from seeking capital. Amongst those households seeking credit in the 24 months prior to my survey, 43.8% of all households had borrowed sufficiently, 30% borrowed amounts less than the value they demanded, and 7.5% were denied by credit providers. Overall, three quarters of the surveyed households borrowed in the 24 months prior to the survey (304 households).[41] Almost all households had loans in both periods; 0-12 months and 12-24 months prior to the survey.

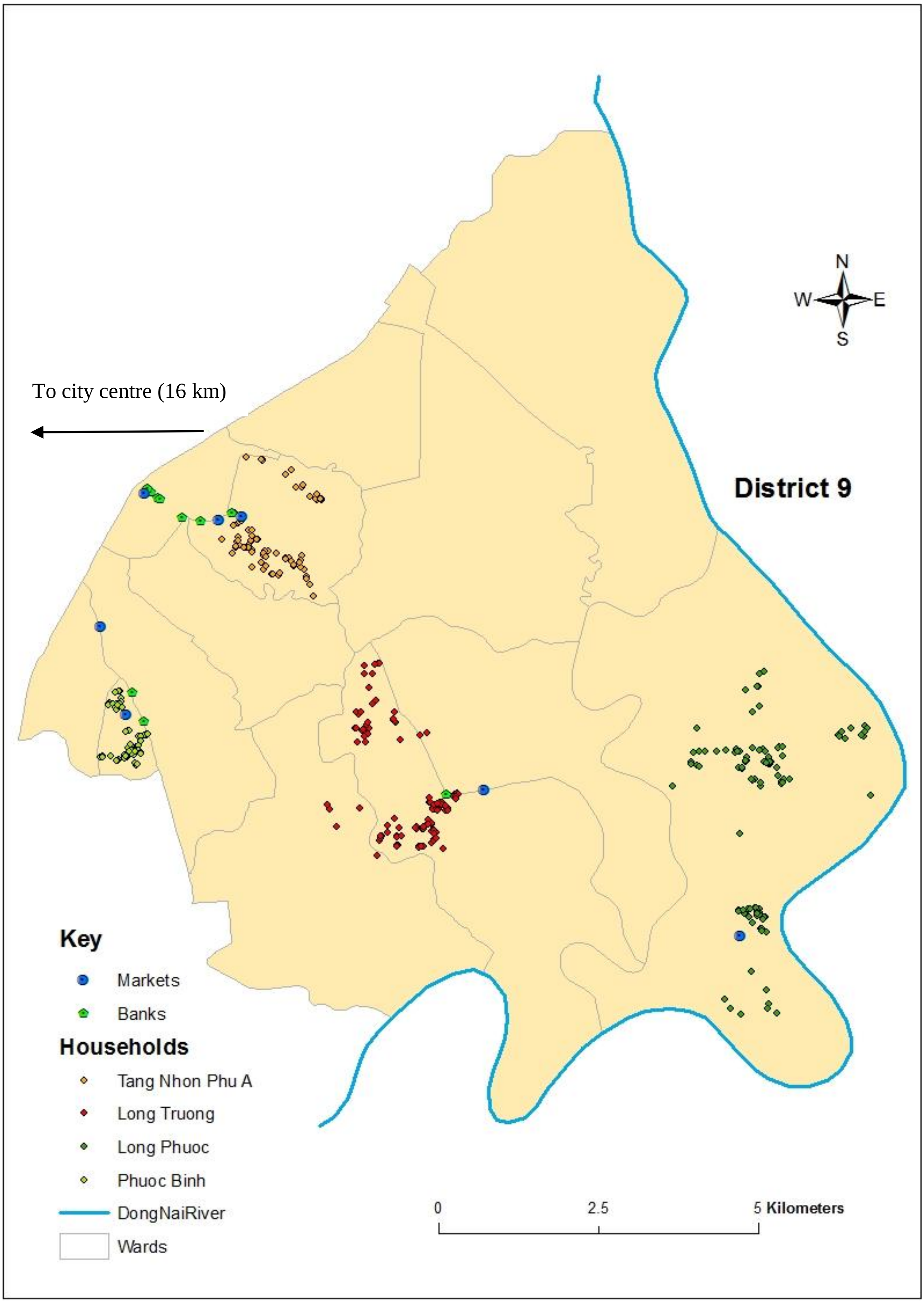
For credit participation, I simply treated households as borrowers if they had at least one loan during the 24 months prior to the survey, and otherwise they were classified as non-borrowers. Meanwhile, potential borrowers are often excluded, discouraged, rejected, or rationed to smaller loans relative to what they might have optimally demanded; these potential borrowers are deemed credit-constrained. Accordingly, the number of credit-constrained households, unconstrained households, and credit participants were estimated and presented in Table 4.4. Although there are more than ten banks and credit institutions in the surveyed areas, the poor are highly credit-constrained (48% of the surveyed households). Since approximately 45% of the poor's loans were from the informal credit sector, and the poor might have been excluded from the formal credit, I could regard them as the formal credit-constrained. If that is true, the incidence of credit constraints would be higher than the current estimates suggest.

Finally, Table 4.5 provides some preliminary information about differences between borrowers and non-borrowers. Overall, the borrowers and non-borrowers are no different in terms of occupations, gender, education, and marital status of the household head, access to internet/newspapers, TV/radio ownership, initial income, and assets acquired more than 24 months prior to the survey. However, the borrowers are

[41] Households often borrowed more than one loan, some loans during the past 12 months, some loans somewhere between 12 and 24 months prior to the survey.

younger, have bigger households and more young household members, and own fewer assets acquired during the two years preceding the survey.

Figure 4.1: Study household and financial facility locations in District 9



Note: DongNai River is a large river and there is no bridge between District 9 and other side (DongNai province) of the river. All banks and credit institutions in the district appear in the green pentagons.

In addition, borrowers tend to dwell in more rural wards and further away from markets and banks. We used GPS receivers to collect data on coordinates of each household and facility such as bank branch and market in order to estimate distance from each household to the nearest market and nearest bank. Figure 4.1 shows that there are many bank branches and credit institutions in the urban wards (or nearby) of Tang Nhon Phu A (TNPA) and Phuoc Binh (PB), while only one bank branch in the rural ward of Long Truong (LT) and no bank branch in (or nearby) the other surveyed rural ward of Long Phuoc (LP). Similarly for market presence, only one market in each rural ward, but many in urban wards or nearby. Clearly, the proximity to financial institutions does not help the poor to have access to credit. Other barriers rather than the proximity may play a role in obstructing the poor on the way to obtaining credit.

4.4.2 Determinants of credit participation by the poor: An econometric analysis

4.4.2.1 The Probit estimates

Estimates from probit models of the determinants of credit participation are presented in Table 4.6. Because of highly heterogeneous population density across the wards and possible multicollinearity between ward dummies and distance to the nearest banks (which vary mainly by ward), three separate estimation models are reported.

The estimates reveal several determinants of credit participation by the poor in peri-urban areas. Households with older heads and those currently married have a lower probability of borrowing. The fact is that households with unmarried-heads have smaller household size and have to borrow to smooth consumption when they have adverse shocks because they have lower ability to increase income from labour (Kochar, 1995, 1999). Indeed, the estimates show that larger households are more likely to be borrowers, perhaps because they maybe have lower credit risks because they have more relationships with community and more diversified sources of income (Schreiner & Nagarajan, 1998). It is also the case that initially richer households are more likely to be borrowers. The pre-survey income per capita, which is closely associated with labour income of the poor, has a significantly positive impact on credit participation. In addition, phone ownership that represents household wealth through the ability to afford phone bills and connection fees, and represents better conditions to communicate and maintain social networks, also positively influences credit participation (Table 4.6). In contrast, total values of fixed assets such as house, land,[42] and other durable asset acquired over the 24 months prior to the survey have no impacts on borrowing (Table 4.6, columns 1, 2 and 3). The poor in peri-urban areas often lack or have incomplete

[42] No single household acquired land and house within the last 24 months from the survey.

legal documentation for the assets, e.g. land-use right certificates and house ownership certificates (Kim, 2004) because they do not have money to pay fees and do not know how and where to get the certificates done, hence the assets are unable to be lodged as collateral for their desired loans.

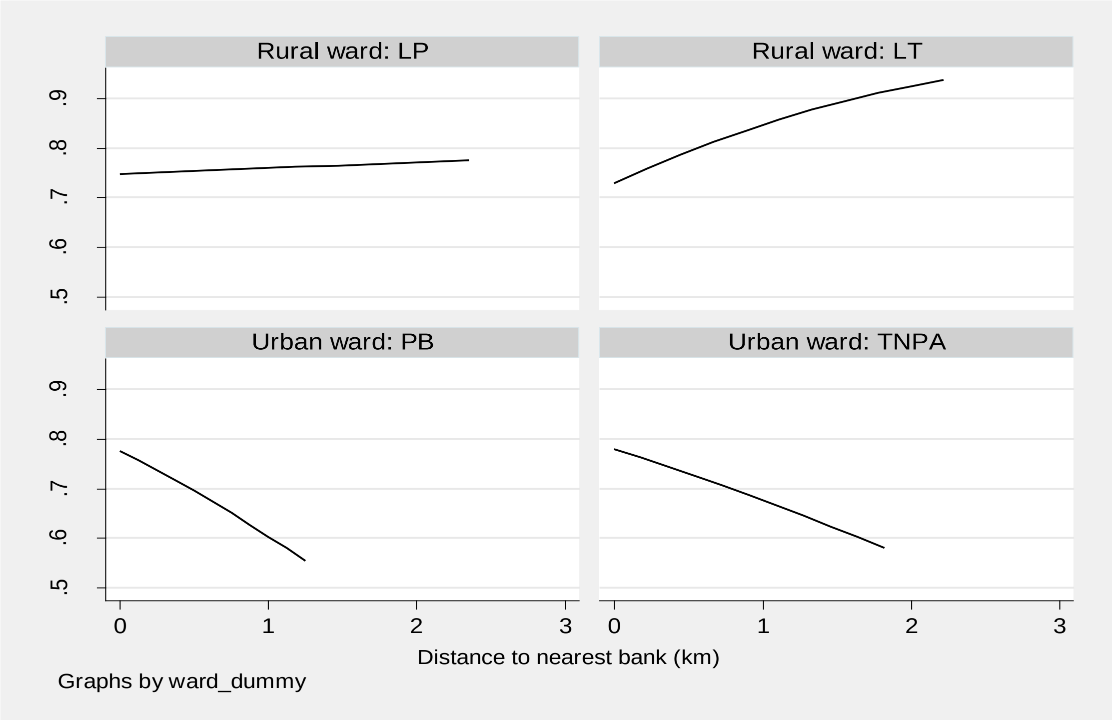
There is no gender bias in microcredit participation in the peri-urban areas, contrast to what is found in rural Vietnam by Barslund and Tarp (2007) and Nguyen (2007). My results also show that education of household heads does not significantly influence credit participation. The poor's household heads in my survey have low education, only 5.5 years of schooling compared to 8.9 years of schooling for general household parents in Vietnam surveyed in 2006 (VHLSS, 2006). Moreover, these poor household heads usually work in unskilled sectors, such as small trade, factory workers, housewives and casual workers, where education is not rewarded well. My finding is contrary to other studies from other developing countries where education has an important role in credit participation (Swain, 2007; Zeller, 1994).

Households' dwelling location is an important determinant of credit market participation in the peri-urban areas. Almost all loans by the poor are small, collateral-free, and mainly based on social capital or interpersonal trust. Households in the more rural parts of the peri-urban area have better social capital than more urban households, thus they have higher likelihood of credit participation. This is shown by the significantly positive coefficients on the two rural wards, Long Truong (LT) and Long Phuoc (LP), in column 1 of Table 4.6.[43] When exploring the role of distance within each ward, in the rural ward of LT, households that are far away from the nearest bank (also far away from the ward centre where households are more urban) are also found more likely to borrow (Figure 4.2).[44] This re-confirms the role of social relationship and interpersonal trust in credit transactions in peri-urban areas.

[43] Inclusion of distance to nearest market (interacted with ward dummies) in the models gives the similar result as distance to nearest bank, thus I do not report results of the regression with the distance to nearest market.

[44] In LT ward, households living far away from the centre are rural household farmers or casual workers, while households near the ward centre are small traders, grocery shop keepers. In LP ward, all households are involved in rural economic activities.

Figure 4.2: Predicted probabilities of credit participation by distance to the nearest bank



The data exploration shows that most borrowing households (56%) in urban wards (TNPA and PB) borrowed from the formal (subsidised) credit channels, in contrast, most borrowing households in rural wards (LT and LP) borrowed from the informal credit sector. This means that the more rural poor households rely more on informal credit, whereas their more urban counterparts rely on government subsidised funds.

The impact of distance to the nearest banks and main sources of the poor's credit in rural and urban areas could imply that households far away from ward centres (dwelling in rural countryside) could have better community relationships and interpersonal trust; better social capital helps to ease access to informal credit sources, such as relatives, neighbours, friends, and other providers who mainly lend money on the basis of interpersonal trust rather than collateral.

The proportion of borrowing neighbours influences negatively and significantly the likelihood of borrowing in urban wards (TNPA and PB), but not in rural wards (LT and LP) (Table 4.6, column 2). This implies that households in urban areas compete against their neighbours in accessing limited credit resources from subsidised funds, but this is not the case in the rural wards because the poor there rely more on informal credit.

In summary, household size, younger households, initial income, phone ownership, and living in more rural countryside areas are important determinants of credit participation by the peri-urban poor. On the other hand, gender, education and assets do not matter in credit participation of poor households. Further, households in rural wards with presumably better relationships and interpersonal trust have advantages in accessing credit, especially informal credit. Competition by other borrowing neighbours in accessing credit resources, especially subsidised funds, is also an influential factor for credit participation by the poor in urban areas.

4.4.2.2 Tobit Type 2 for loan amounts received by the poor

The Tobit model estimates in Table 4.7 reveal some key findings: *First*, gender does not really matter in credit participation as found and discussed in the preceding section, but it plays a role in explaining loan size. Male-headed households received lower amounts of loans than female-headed households. The finding is contrary to the common trend in developing countries because females are often involved in small businesses which need smaller loans (Armendariz & Morduch, 2005, p. 181); however, in peri-urban areas loans are mainly used for non-production so the type of business activity of females may matter less for loan size.

Second, the age of household heads has a slightly positive effect on loan size. The older households tend to receive greater loans, with a maximum at about 46 years old. Very young or very old headed-households have a smaller labour force, and hence have lower ability to earn and repay.[45] Therefore, they may be lent smaller amounts, or they themselves favour smaller loans to fit with their demand and ability to repay.

Third, the initial income per capita and household sizes are important determinants of loan size because an increase in household size would help to increase labour income and diversify income sources (Schreiner & Nagarajan, 1998), and also increase demand for consumption. *Finally*, education level of household heads, head's marital status, assets acquired prior to borrowing, location dummies, distance to the nearest banks and the proportion of borrowing neighbours make no significant difference to loan sizes.

4.4.2.3 The Multinomial Logit estimates for credit participation

The binary Probit models help examine the roles of household characteristics and endowments in credit participation regardless of credit sources and of possibly different roles of each factor in specified credit market segments. Pooling credit market segments would conceal the roles of each factor. Therefore, to provide more nuanced insights, the surveyed households are classified into four groups: Non-borrowing, borrowing from

[45] Scatter plot of household size against head's age or regression household size on head's age and head's age squared give a clear inverse U-shaped relationship between household size and head's age.

informal credit, borrowing from formal credit, and borrowing from both informal and formal credit. The Multinomial Logit model (MNL) is then employed to examine factors influencing the probability of specified credit participation.

Amongst 411 households, 26.0% of the surveyed households did not borrow, 23.6% borrowed from only informal sources, 25.3% borrowed from only formal sources, and 26.0% borrowed from both formal and informal credit. The purpose of the MNL model is to compare each outcome probability with the base outcome of the non-borrower group. The estimates are presented in Table 4.8, in the form of the relative risk ratios (RRR).

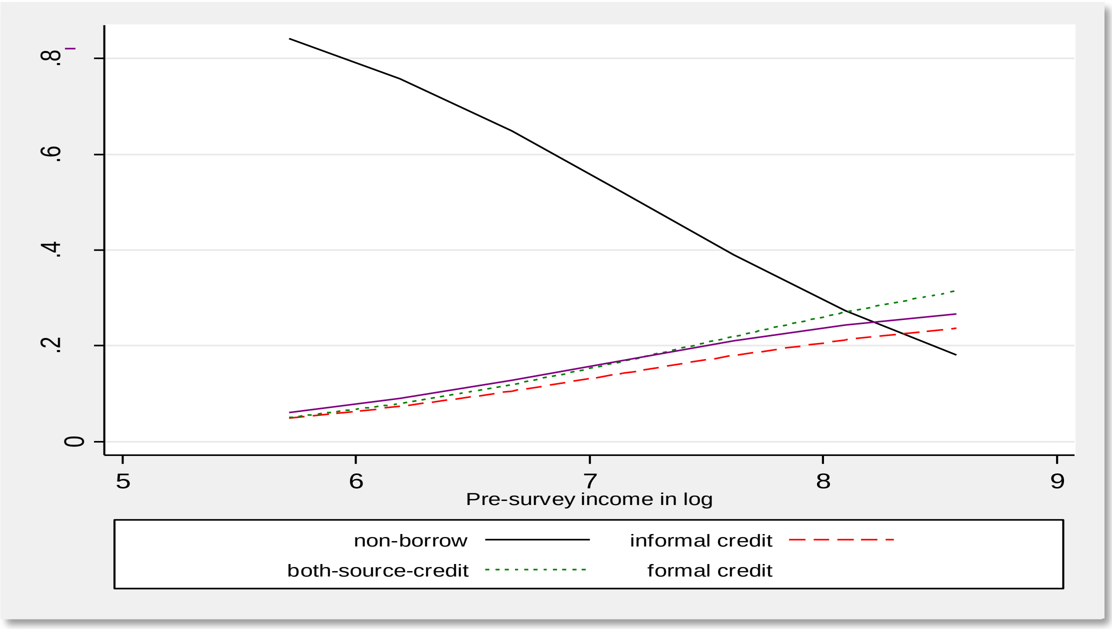
Household heads' gender and age

To interpret the estimated coefficients, I provide two illustrations by using a dummy (e.g. gender) and a continuous variable coefficient (e.g. age). The head's gender coefficient $e^{\beta1}$ =1.3865 (Table 4.8, Model 1, column 1) means that the probability of borrowing from informal credit by males is 38.65% (i.e. 1.3865-1.00) higher than for females. Similarly, $e^{\beta3}$ = 0.8756 means that the probability of borrowing from formal credit by males is 12.44% (i.e. 0.8756-1.00) lower than for females. Nevertheless, the effect of head's gender is not statistically significant across models and credit market segments. For a continuous variable of head's age, the RRR is about 0.96 across models and sources of credit, smaller than one, meaning that when a household head gets an additional year older the ratio of credit participation probability will decline by about 4%, keeping other things constant.

Household size, phone ownership, and pre-survey income

The estimates show that the ratios of borrowing probability increase with household size in all credit market segments. Greater household size represents a bigger demand for consumption and a better ability for income generation and debt repayment. Similarly, having a phone has a positive influence on the likelihood of participation in all credit markets, but the effect is highly significant *only* in the formal credit market. Owning a phone has advantages to communicate and obtain information about formal credit sources, and also proxies for household wealth through affordability of connection charges and phone bills. Similar to phone ownership, the pre-survey income per capita positively affects credit participation in all credit market segments (Table 4.8 and Figure 4.3).

Figure 4.3: Predicted probabilities of participation in specified credit sources by pre-survey income (in logarithm)



Note: The slope-downward line depicts the declining probability of being non-borrowers as the income increases.

Marital status of household heads

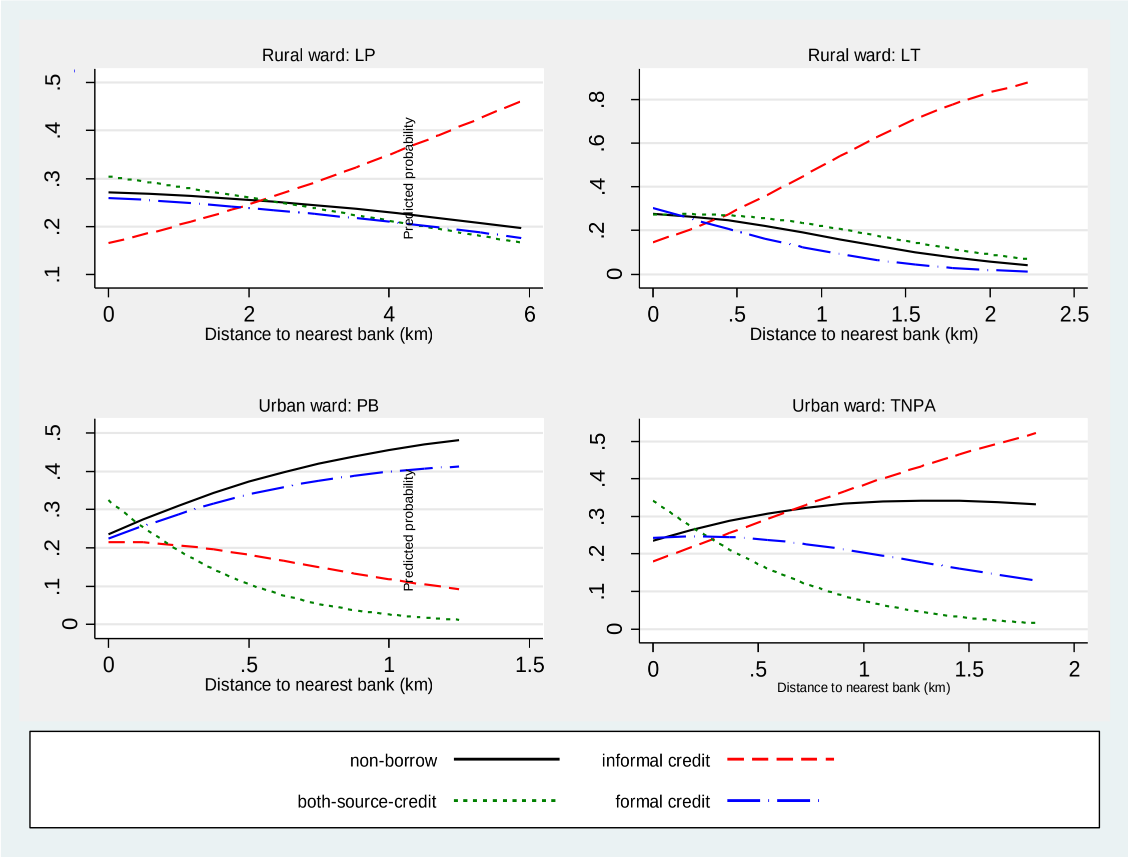
As expected, single-head households such as the divorced, separated, widowed and unmarried tend to borrow more from informal credit than the current married-head households. These single-head households are often older-headed households who have less ability to smooth consumption by themselves if they face adverse shocks, especially demographic shocks, because they do not have enough working household members to increase income by increasing labour working hours. Therefore they are forced to borrow especially from informal credit as discussed in Kochar (1995). This variable is a demand-side factor.

Household dwelling locations and distance to the nearest banks

In addition, loans to the poor are small, collateral-free, and based mainly on social capital or interpersonal trust. As discussed earlier, households in the rural wards have more advantages compared to urban households when accessing *informal* and both-credit sources, hence the ratio of credit participation probability in informal and both-credit-sources by households in rural wards (LT and LP) is higher (Table 4.8, Model 1). So the distance and dwelling locations are demand-side factors since the distance and locations proxy for degree of rurality and people in rural areas have more outside options as they can get informal credit easier thanks to tighter community relationships.

In contrast, greater distance and living in rural areas may increase the physical barriers to getting formal credit, so the distance and rural living locations would be supply factors. However, household dwelling locations and distance to the nearest bank do not affect the ratios of probability of *formal* credit participation. In other words, formal credit is evenly distributed across wards (Table 4.8, Model 1, column 3) and within each ward (Table 4.8, Model 3, column 3). When considering distance to the nearest banks within each ward, the distance does not significantly affect the ratio of probability of informal credit participation in the *urban* wards, but it positively affects the ratio of probability of informal credit participation in *rural* wards. In other words, the ratios of probability of informal credit participation increase significantly with distance to the nearest banks *only* in rural wards (Figure 4.1 and Figure 4.4). Once again, the *degree of rurality* as a demand-side factor plays a important role in getting informal credit even in rural ereas.

Figure 4.4: Predicted probabilities of participation in specified credit sources by distance to the nearest bank



The upward-slope of the curves indicates that the probability of participation in a specified credit markets will increase with the distance from each household to the nearest bank. However, the multinomial Logit models report the ratio of probability of a specified credit participation and probability of being in the base (non-borrowing) group. Therefore, the gap between each curve for a particular borrower group and the base curve becomes the issue of interest, for example the gap between informal credit borrowing (the red dashes) and the base curve of non-borrowing (solid-curve) represents the ratio of the probability of informal credit participation and the probability of being in non-borrowing group. In rural wards (two top panels of Figure 4.4), the gaps become larger when households dwell far away from banks which are often located at ward centres. These households have easier access to informal credit thanks to possibly tighter community relationships and higher interpersonal trust.

In short, households in rural wards have greater propensity to borrow from informal credit compared to urban households; and within a rural ward, households far away from ward centres, more rural, rely more on informal credit because of either better social relationship. These demand-side factors play more important roles in accessing informal credit.

Proportion of borrowing neighbours: Competition or crowding-out effects

The estimates of the interactions between the proportion of borrowing neighbours and ward dummies reveals that there is a crowding-out effect from the neighbours in accessing *only* formal (subsidised) credit in all the wards. For example, the RRR is 0.0159 (Table 4.8, Model 2, column 3), meaning that when the rate of borrowing neighbours in LP ward increases by 10 percentage points the ratio of formal credit participation probability will decline by about 9.8% [i.e. (1.00-0.0159)x10%], keeping other things constant.

Other insignificant factors

Controlling for other variables, education and the initial assets play no significant roles in credit participation even in the formal credit sector. However, as previously discussed, most formal credit to poor households in the studied areas are from the government subsidised funds, such as the HEPRF, VBSP, and other supporting funds, but very few of the loans are from commercial banks. Consequently, the key lenders require neither collateral nor specific education when making lending decisions.

In summary, age, household size, and pre-treatment income have important roles in all credit market segments. In contrast, gender, education, and pre-survey assets are found to have no role in explaining credit participation in any specified credit market segments. The household location, phone ownership, and marital status of household heads have different roles in different credit segments for the poor in the peri-urban areas. Finally, credit subsidies may lead to credit demand excess and crowding-out effect amongst the borrowers.

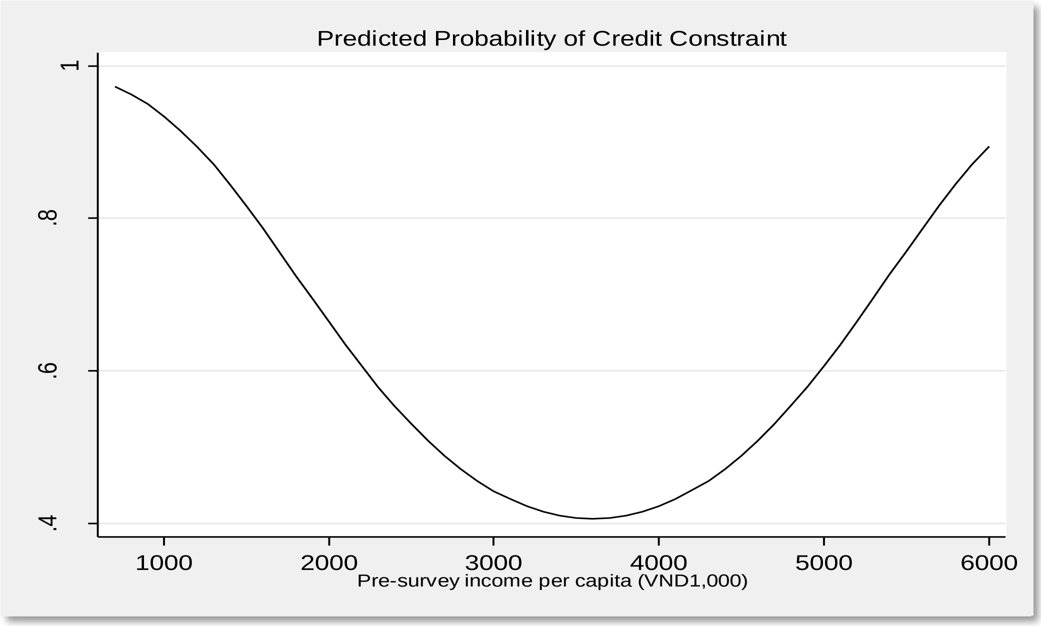
4.4.3 Determinants of credit constraints of poor households

Though 74% of surveyed households borrowed, the predicted probability of credit constraints is high, at 48% (Table 4.9). If credit constraints are more related to the credit supply side, then the determinants of credit constraints could be more related to obstacles in the credit markets of developing countries. Similar to Crook and Hochguertel (2005), Jappelli (1990), Magri (2002), and Thaicharoen et al (2004), I find that higher income reduces the likelihood of being credit-constrained, even though all my study households were poor.

Surprisingly, the income also has a U-shaped effect on the probability of credit constraints (Figure 5) with the minimum probability at the income level of about VND 3.5 million (about US$210). This U-shaped effect of income on credit constraints is contrary to Chen and Chivakul (2008) who found the inverted-U shape effect for general households rather than the poor in Bosnia and Herzegovina. All households in my sample were poor and most of them borrowed from informal and preferred formal credit; extremely poor households, however, were excluded by both informal lenders and government subsidised funds.[46] Therefore, the higher is income per capita the lower the credit constraints. On the other hand, households whose income per capita is higher than VND 3.5 million were more credit-constrained as income increased. As we learned previously, 96% of credit to the poor was from small credit sources (small subsidized credit and informal credit). Thus, the credit constraints from the income level of VND 3.5 million onward could not be due to the exclusion by the microcredit lenders but due to higher demand for credit to finance bigger projects, businesses or spending but these households were lent less than what they really wanted to borrow (partial borrowers). This group of households should be financed by (bigger) formal credit, especially commercial banks, but their demand for credit was not yet met, and hence the households were still credit-constrained. This finding also suggests that if subsidised formal credit funds lend the poor households, the credit amounts should not be fixed for all the poor but should vary according to their income levels, at least two fixed amounts, one amount for households whose income is below VND 3.5 millions and one amount for households whose income is above VND 3.5 million.

[46] According to local HEPRF officers, even all the poor are eligible for preferred loans, they did not lend to the extreme poor because the households could not repay. They should have received direct assistance rather than credit.

Figure 4.5: Predicted probabilities of credit constraints by pre-survey income per capita



In addition to income, in the Vietnamese context, assets such as land, house and durable fixed assets mainly represent household wealth because households usually lack investment choices for their savings due to unstable capital markets and high inflation (Barslund & Tarp, 2007). In my surveyed areas, fast industrialisation and urbanisation have caused real estate to be more marketable and increase property values. This enabled the poor to access credit because lenders may consider the property or fixed assets as collateral, if asset owners have legal documentation, when they sort out their clients (Crook & Hochguertel, 2005; Kedir et al, 2007; Jappelli, 1990; and Zeller, 1994). Without documentation the assets are not used as collateral, but the assets may indicate potential repayment ability because the peri-urban and urban poor also have informal property transactions without legal documents since informal property markets function well in developing countries including Vietnam (Kim, 2004; Mooya & Cloete, 2007). As a result, the households owning higher asset values are less likely to be credit-constrained because the assets can be informally sold to repay debts even though they are not able to be lodged as collateral when borrowing.

Contrary to Barslund and Tarp (2007), Izumida and Pham (2002), Kedir et al, (2007), Jappelli (1990), and Zeller (1994), the credit-constrained and unconstrained households are homogenous in terms of household heads' gender, age, education, marital status, and household size,[47] perhaps because the current study focuses on the poor rather than general population. In addition, the probability of the constraints is not

[47] I also checked with household labour force (persons aged 18-60 years old), the estimation result is similar to the case of household size.

different across wards, and not affected by the proportion of borrowing neighbours (Table 4.9, Model 2).

Finally, households dwelling far away from banks within each ward had a higher probability of being credit-constrained. The effect of the distance to the nearest bank is significant for TNPA, PB, and LT wards, but is not for LP ward (Table 4.9, Model 3). LP ward is a purely rural area where the distance does not obstruct the poor households from credit resources, and the likelihood of credit participation and credit constraints are not determined by where the households are situated. Better community, relatives, neighbouring relationships and interpersonal trust may help households in pure rural areas like LP ward to have not only a higher probability of credit participation (Table 4.6), especially credit from informal sector, but also lower the likelihood of being credit-constrained (Table 4.9) compared to the other wards in the areas. This suggests that community mutual help systems through credit could do a good job in smoothing consumption and investing in healthcare and children's schooling. On the other hand, given the condition of weak community relationships in more urban wards, poor households find it hard to borrow and are highly credit-constrained. Subsidised funds are usually the last resort for lenders to help the poor in the urban areas.

For the purely rural ward of LP, the distance to the nearest bank does not affect the probability of credit participation and credit constraints. This finding is consistent with Barslund and Tarp (2007, p. 499) who find that distance to district centres where there are bank offices does not affect the likelihood of credit rationing in rural Vietnam. On the contrary, in my case, all poor households sited near banks in the urban wards have lower probability of being credit-constrained. Thus, it suggests that one would better consider the effect of distance within each region or area (i.e. using interaction terms between the distance and dummy of areas) rather than compare across various areas because each area has its own socio-economic conditions, and thus distance matters in credit constraints in some certain areas.

4.5 Summary of findings

Examining factors affecting credit participation and credit constraints in peri-urban areas in Vietnam reveals: *First*, the presence of many commercial banks does not help the poor to access to formal credit, and hence the poor in the peri-urban areas rely heavily on informal credit. Furthermore, unlike the usage pattern of loans in rural Vietnam, loans in the peri-urban areas are mainly used for consumption. *Second*, households in rural wards have a higher probability of borrowing than their counterparts in the urban wards because of better social relationships in rural areas. Moreover, competition from borrowing neighbours adversely affect the propensity of borrowing *only* in urban wards where the poor depend more on government subsidised credit funds, which are limited.

Third, a closer look at specified microcredit sources reveals that the roles of marital status, communication facilities, dwelling places, and competition from neighbours vary across different credit market segments. Accordingly, married-head households tend to avoid informal credit, whereas the better-communicating households borrow more from formal credit lenders. Households far away from banks were unable to borrow from the formal credit resources; however, these households in rural areas were more likely to borrow from informal credit lenders. Moreover, the competition among households exists *only* in formal credit markets which provide mostly subsidised credit loans. Overall, pooling formal and informal credit market segments would blur the picture of determining factors of credit participation.

Finally, wealthier households in terms of asset holdings and phone ownership amongst the poor group appear less credit-constrained. The likelihood of both credit participation and credit constraints increases with distance to the nearest banks, which implies that households living far away were able to borrow but their credit amounts were less that their optiomal amounts since they mainly borrowed from informal (and also small) credit. This suggests that supply-side intervention could help in overcoming credit constraints. Overall, the poor in urban wards are slightly more credit-constrained due to exclusion by commercial banks, and by informal credit presumably due to weak community relationships and interpersonal trust.

There remain some caveats in this study; the determinants of credit participation and constraints would come from the unobservable attributes such as households' entrepreneurial ability, attitude to risks, and access to social networks, which are assumed to be associated with pre-survey incomes and assets in this study. Further advances on the current research should control for these attributes by employing fixed effects methods on panel data to confirm the finding in this chapter.

TABLES

Table 4.1: Sources and sizes of loans by credit provider

Sources of loans	Frequency (no of loans)	Percent in total (%)	Mean (VND 1,000)	Standard Deviation
Formal credit	**336**	**55.26**	**9,327**	**33,421**
VBSP (1)	37	6.06	9,622	15,764
Agribank (2)	18	2.96	26,444	46,482
Other commercial banks (3)	8	1.32	119,000	176,254
JCSF (4)	29	4.77	4,564	3,655
Social political organisations (5)	62	10.20	4,564	3,472
HEPRF (6)	182	29.93	5,176	4,189
Informal credit	**272**	**44.74**	**5,229**	**12,760**
Moneylenders, ROSCAs, pawnbrokers, others (7)	51	8.39	9,218	15,870
Friends, relatives, neighbours (8)	221	36.35	4,308	11,780
Overall	608	100	7,494	26,330

Source: own calculation from author's survey;
VBSP: Vietnam Bank for Social Policies; JCSP: Job Creation Support Fund; HEPRF: The Hunger Elimination and Poverty Reduction Funds; ROSCAs: Rotating savings and credit associations

Table 4.2: Sources, sizes and interest rates of loans

Credit sector	Percent in total (%)	Loan sizes (VND 1,000)		Monthly interest rates (%)	
		Mean	Std.Dev	Mean	Std.Dev
By formal/informal sector					
Formal	55.26	9,327	33,421	0.78	0.70
Informal	44.74	5,229	12,760	2.14	5.93
Friends, relatives & neighbours	36.35	4,308	11,780	0.033	0.27
Other informal sources	8.39	9,218	15,870	11.29	9.22
By preferred sources					
Preferred loans	51.00	5,503	6,725	0.76	0.72
Non-preferred loans	49.00	9,564	36,897	2.05	5.67
Overall	100	7,494	26,330	1.40	4.05

Source: own calculation from author's survey
Notes: Preferred loans include items 1, 4, 5, and 6, and Non-preferred loans are of 2, 3, 7, and 8 in Table 4.1.

Table 4.3: Shares and sizes of loans by purposes

Purpose of loans	Percent in total (%)	Mean (VND 1,000)	Standard deviation
Production/business	**26.64**	**6,512**	**5,729**
Non-production	**73.36**	**7,850**	**30,550**
Consumption	30.92	3,163	4,846
Debt payment	4.61	14,661	37,752
House acquisition/repairs	3.62	40,977	63,517
Schooling fees	16.94	3,665	2,239
Health care	16.12	11,346	51,013
Others	1.15	15,143	17,478
Overall	100	7,494	26,330

Source: own calculation from author's survey
Note: Exchange rate in USD/VND = 16,481

Table 4.4: Demand for credit, credit participation and credit constraints

Specified categories	Number of households	Percent in total (%)
Household has demand for credit in the past 24 months prior to the survey?	**411**	**100**
No, do not want to borrow	**76**	**18.49**
Sufficient capital, no need credit (a)	35	8.52
Discouraged households (b)	41	9.97
Yes, households need capital	**335**	**81.51**
Was not lent any money (denied) (c)	31	7.54
Was lent amounts less than what households wanted (d)	124	30.17
Was lent fully (e)	180	43.80
Credit participation in the past 24 months	**411**	**100**
Borrowers (d & e)	304	73.97
Non-borrowers (a, b & c)	107	26.03
Credit constraints	**411**	**100**
Credit-constrained (b, c & d)	196	47.69
Credit-unconstrained (a & e)	215	52.31

Source: own calculation from author's survey

Table 4.5: Means of some main variables and *t*-values for equal means by borrowing status

Variable	Borrowers		Non-borrowers		*t*-value
	Mean	Std. Dev	Mean	Std. Dev	
Job (favourable jobs=1)	0.122	0.327	0.140	0.349	0.48
Head's sex (male=1)	0.507	0.501	0.505	0.502	0.03
Head education (year)	4.911	3.35	4.664	3.76	0.60
Head's married (yes=1)	0.648	0.478	0.607	0.491	0.74
Head's age	52.901	13.97	59.467	15.46	3.87**
Household size	5.191	2.343	4.523	2.597	2.34*
Child under 6 years old (yes=1)	0.309	0.463	0.178	0.384	2.89**
Children aged 6-18	1.118	1.024	0.869	1.100	2.05*
Persons aged 18-60	3.230	1.694	2.692	1.793	2.71**
Older-than-60 person (yes=1)	0.352	0.478	0.533	0.352	3.25**
Rural area (LT & LP =1)	0.635	0.482	0.477	0.502	2.83**
Distance to nearest bank (Km)	2.226	2.098	1.804	1.900	1.92+
Distance to nearest market (Km)	1.409	1.032	1.085	0.872	3.10**
Have a phone (yes=1)	0.809	0.394	0.644	0.481	3.18**
Internet/newspapers (yes=1)	0.053	0.224	0.037	0.191	0.68
Have a TV and radio (yes=1)	0.944	0.230	0.925	0.264	0.66
Durable & fixed assets acquired within 24 months prior to survey	4,372	6,264	9,057	11,693	2.78**
Durable & fixed assets acquired over 24 months prior to survey	849,924	821,335	786,097	795,593	0.71
Pre-survey income per capita	3,592	814	3,505	925	0.86

Notes: t statistics significant at 10% (+), 5% (*), and 1% (**); assets, income, and expenditure are in VND 1,000.

Table 4.6: Marginal effects on the probability of credit participation (Probit estimation)

Explanatory Variables	Model (1)	Model (2)	Model (3)
Head's sex (male=1)	-0.0285	-0.0302	-0.0211
	(0.55)	(0.59)	(0.41)
Head's age (years)	-0.0073	-0.0072	-0.0073
	(4.29)**	(4.28)**	(4.32)**
Head's education (years of schooling)	0.0017	0.0019	0.0027
	(0.22)	(0.27)	(0.37)
Marital status (married=1)	-0.1033	-0.0974	-0.1094
	(1.86)+	(1.75)+	(1.95)+
Household size in log[(a)]	0.1932	0.1951	0.1932
	(3.56)**	(3.63)**	(3.59)**
Pre-survey income per capita in log	0.1781	0.1730	0.1884
	(2.15)*	(2.13)*	(2.28)*
Pre-survey assets in log (assets acquired over 24 months prior to survey)	-0.0010	0.0018	-0.0014
	(0.06)	(0.11)	(0.09)
Phone ownership (yes=1)	0.1309	0.1232	0.1389
	(2.26)*	(2.14)*	(2.34)*
Phuoc Binh – PB (urban)	0.0185		
	(0.27)		
Long Truong – LT (rural)	0.1570		
	(2.58)**		
Long Phuoc – LP (rural)	0.1146		
	(1.95)+		
Interaction terms			
Borrowing neighbour proportion x TNPA		-0.6642	
		(1.95)+	
Borrowing neighbour proportion x PB		-0.5928	
		(1.81)+	
Borrowing neighbour proportion x LT		-0.3297	
		(1.14)	
Borrowing neighbour proportion x LP		-0.3921	
		(1.35)	
Distance to nearest bank (Km) x TNPA			-0.0968
			(1.20)
Distance to nearest bank (Km) x PB			-0.1534
			(1.06)
Distance to nearest bank (Km) x LT			0.1277
			(2.09)*
Distance to nearest bank (Km) x LP			0.0113
			(0.70)
Wald χ^2	44.56**	46.80**	53.35**
Prob> χ^2	0.0000	0.0000	0.0000
Predicted probability at x bar	0.760	0.761	0.763
Pseudo R-squared	0.12	0.12	0.13
Observations	411	411	411

Notes: Robust z statistics in parentheses; statistically significant at 10% (+), at 5% (*), and at 1% (**). Tang Nhon Phu A (TNPA) ward is set as a base for ward dummies. [(a)] *The marginal effect of household size (hhsize) on the predicted probability is calculated as, suppose* $Y=\alpha + \beta.\ln(hhsize)$*, so that* $dY/dU = dY/d(hhsize)= \beta.(1/hhsize)$*, keep other things equal.*

Table 4.7: Interval regression (Tobit Type 2) for loan amounts received

Explanatory Variable	Model (1)	Model (2)	Model (3)
Head's sex (male=1)	-3,962.37	-3,977.1	-3,762.87
	(2.01)*	(2.02)*	(1.92)+
Head's age (years)	528.75	525.4	500.85
	(1.45)	(1.43)	(1.37)
Head's age squared	-5.57	-5.50	-5.38
	(1.78)+	(1.75)+	(1.72)+
Head's education (years)	147.38	153.9	142.50
	(0.51)	(0.53)	(0.47)
Marital status (married=1)	1,972.25	2,041.4	1,762.18
	(0.90)	(0.94)	(0.81)
Household size in log	4,621.38	4,631.5	4,636.29
	(2.48)*	(2.48)*	(2.43)*
Pre-survey income per capita in log	7,322.34	7,252.5	7,272.70
	(2.01)*	(2.02)*	(1.98)*
Pre-survey assets in log (assets acquired	624.64	653.2	572.99
over 24 months prior to survey)	(1.14)	(1.19)	(1.04)
Phone ownership (yes=1)	5,024.36	4,963.4	4,965.04
	(2.89)**	(2.85)**	(2.81)**
Phuoc Binh – PB (urban)	-1,606.15		
	(0.61)		
Long Truong – LT (rural)	2,389.45		
	(1.09)		
Long Phuoc – LP (rural)	874.92		
	(0.41)		
Interaction terms			
Borrowing neighbour proportion x TNPA		-6,635.6	
		(0.82)	
Borrowing neighbour proportion x PB		-8,489.4	
		(1.15)	
Borrowing neighbour proportion x LT		-2,397.1	
		(0.38)	
Borrowing neighbour proportion x LP		-4,124.7	
		(0.60)	
Distance to nearest bank (Km) x TNPA			-2,526.62
			(0.87)
Distance to nearest bank (Km) x PB			-7,899.71
			(1.53)
Distance to nearest bank (Km) x LT			304.95
			(0.18)
Distance to nearest bank (Km) x LP			-280.37
			(0.54)
Constant	-85,633	-81,289	-81,505
	(2.40)*	(2.25)*	(2.28)*
Wald χ^2	28.32**	29.42**	27.22*
Prob> χ^2	0.0050	0.0057	0.0116
Sigma (test for Tobit model)	13720.32	13722.66	13715.53
	(8.90)**	(8.89)**	(8.94)**
Observations	405	405	405

Notes: Robust z statistics in parentheses; statistically significant at 10% (+), at 5% (*), and at 1% (**). Five extreme outliers (of loan amounts) are dropped.

Table 4.8: The multinomial Logit estimation with Relative Risk Ratios for credit participation in specified credit sources

Explanatory Variables	Model 1			Model 2			Model 3		
	RRR[(b)] Outcome for			RRR Outcome for			RRR Outcome for		
	Informal Credit	Both-source Credit	Formal Credit	Informal Credit	Both-source Credit	Formal Credit	Informal Credit	Both-source Credit	Formal Credit
	22.63%	26.03%	25.30%	22.63%	26.03%	25.30%	22.63%	26.03%	25.30%
Head's gender	1.3865	0.5995	0.8756	1.3846	0.6006	0.8604	1.6307	0.6397	0.8694
(male=1)	(0.87)	(1.43)	(0.36)	(0.87)	(1.43)	(0.41)	(1.23)	(1.25)	(0.38)
Head's age	0.9534	0.9628	0.9641	0.9539	0.9633	0.9644	0.9524	0.9614	0.9645
	(3.81)**	(3.38)**	(3.07)**	(3.79)**	(3.35)**	(3.03)**	(3.79)**	(3.48)**	(3.05)**
Head's education	0.9523	1.0346	1.0179	0.9555	1.0381	1.0165	0.9598	1.0311	1.0264
(years)	(0.91)	(0.67)	(0.35)	(0.85)	(0.74)	(0.32)	(0.76)	(0.60)	(0.52)
Marital status	0.3492	0.7396	0.6627	0.3616	0.7390	0.7269	0.3084	0.6911	0.6253
(married=1)	(2.55)*	(0.76)	(1.01)	(2.47)*	(0.77)	(0.79)	(2.66)**	(0.92)	(1.14)
Household size	2.2269	3.2430	3.3899	2.2499	3.2414	3.4761	2.0855	3.5470	3.3700
in logarithm	(2.17)*	(3.15)**	(3.23)**	(2.20)*	(3.12)**	(3.31)**	(1.96)*	(3.37)**	(3.22)**
Pre-survey income	2.6851	3.7543	2.4145	2.5350	3.4970	2.3867	2.9895	3.2606	2.8708
in logarithm	(1.66)+	(2.11)*	(1.70)+	(1.58)	(2.01)*	(1.65)+	(1.71)+	(2.07)*	(1.99)*
Pre-survey	1.0871	0.9553	0.9591	1.1010	0.9578	0.9756	1.1197	0.9367	0.9351
assets in logarithm	(0.69)	(0.38)	(0.35)	(0.80)	(0.36)	(0.21)	(0.91)	(0.54)	(0.57)
Phone ownership	1.4456	1.7160	3.4660	1.3881	1.6439	3.4750	1.5408	1.7119	3.4014
(yes=1)	(1.00)	(1.45)	(2.98)**	(0.89)	(1.35)	(2.95)**	(1.11)	(1.42)	(2.89)**
PB ward (urban)	0.3026	1.5091	1.3147						
	(1.83)+	(0.80)	(0.63)						
LT ward (rural)	3.3774	6.0195	0.6904						
	(2.68)**	(3.78)**	(0.76)						
LP ward (rural)	1.7661	4.0763	1.2173						
	(1.31)	(3.15)**	(0.46)						

(*Continued next page)*

Table 4.8: The multinomial Logit estimation with Relative Risk Ratios for credit participation in specified credit sources (continued)

Explanatory Variables	Model 1			Model 2			Model 3		
	RRR Outcome for			RRR Outcome for			RRR Outcome for		
	Informal Only	Both sources	Formal only	Informal Only	Both sources	Formal only	Informal only	Both sources	Formal only
	22.63%	26.03%	25.30%	22.63%	26.03%	25.30%	22.63%	26.03%	25.30%
Effects of the proportion of borrowing neighbours within each ward									
Borrowing neighbour proportion x TNPA				0.0258 (1.43)	0.2249 (0.57)	0.0061 (2.31)*			
Borrowing neighbour proportion x PB				0.0058 (2.03)*	0.4571 (0.31)	0.0122 (2.09)*			
Borrowing neighbour proportion x LT				0.2312 (0.67)	2.8864 (0.48)	0.0084 (2.54)*			
Borrowing neighbour proportion x LP				0.1050 (1.02)	1.8797 (0.28)	0.0159 (2.23)*			
Effects of the distance to the nearest bank from households within each ward									
Distance to nearest bank x TNPA							1.4795 (0.68)	0.1511 (2.84)**	0.5846 (1.00)
Distance to nearest bank x PB							0.2846 (0.85)	0.0419 (2.93)**	0.9219 (0.09)
Distance to nearest bank x LT							5.2577 (3.63)**	1.2746 (0.57)	0.5532 (1.09)
Distance to nearest bank x LP							1.2595 (1.85)+	0.9533 (0.45)	0.9895 (0.10)
Wald χ^2	106.20			116.97			114.35		
Prob> χ^2	0.0000			0.0000			0.0000		
Pseudo R2	0.1144			0.1215			0.1288		
Observations	411			411			411		

Notes: Robust z statistics in parentheses; statistically significant at 10% (+), at 5% (*), and at 1% (**); the base outcome (0) is non-borrowing households (non-borrowers which accounts for 26.03% observations).

[(b)]RRR coefficient is exponentiated coefficient = e^{β} = exp(β), e.g. exp(0.3268)=1.3865 where β=0.3268 is the estimated outcome of the standard multinomial Logit model.

Table 4.9: Marginal effects on the probability of credit constraints (probit model)

Explanatory Variables	Model (1)	Model (2)	Model (3)
Head's sex (male=1)	0.0669	0.0676	0.0652
	(1.07)	(1.08)	(1.04)
Head's age (years)	0.0016	0.0016	0.0021
	(0.82)	(0.83)	(1.04)
Head's education (years)	0.0002	0.0006	0.0016
	(0.02)	(0.07)	(0.18)
Marital status (married=1)	-0.0218	-0.0257	-0.0177
	(0.31)	(0.37)	(0.25)
Household size in log	-0.0255	-0.0264	-0.0287
	(0.41)	(0.42)	(0.46)
Pre-survey income per capita	-0.0007	-0.0007	-0.0007
	(3.22)**	(3.20)**	(3.40)**
Pre-survey income per capita squared	1.01e-07	1.01e-07	1.03e-07
	(3.27)**	(3.25)**	(3.47)**
Pre-survey assets in log (acquired over 24 months prior to survey)	-0.0399	-0.0407	-0.0344
	(1.96)+	(2.00)*	(1.67)+
Phone ownership (yes=1)	-0.2171	-0.2158	-0.2070
	(3.33)**	(3.30)**	(3.12)**
Phuoc Binh – PB (urban)	0.0347		
	(0.37)		
Long Truong – LT (rural)	-0.0012		
	(0.01)		
Long Phuoc – LP (rural)	-0.0978		
	(1.28)		
Interaction terms			
Borrowing neighbour proportion x TNPA		0.2815	
		(0.73)	
Borrowing neighbour proportion x PB		0.3216	
		(0.89)	
Borrowing neighbour proportion x LT		0.2406	
		(0.76)	
Borrowing neighbour proportion x LP		0.1234	
		(0.39)	
Distance to nearest bank (km) x TNPA			0.1813
			(1.78)+
Distance to nearest bank (km) x PB			0.3732
			(2.09)*
Distance to nearest bank (km) x LT			0.1685
			(2.30)*
Distance to nearest bank (km) x LP			0.0115
			(0.61)
Wald χ^2	34.99**	34.33**	40.40**
Prob> χ^2	0.0005	0.0011	0.0001
Predicted probability	0.4790	0.4790	0.4790
Pseudo R-squared	0.0700	0.0700	0.0800
Observations	411	411	411

Notes: Robust z statistics in parentheses; statistically significant at 10% (+), at 5% (*), and at 1% (**). Tang Nhon Phu A (TNPA) ward is set a comparison base for ward dummies.

Chapter 5: Impacts of household credit on education and healthcare spending by the poor in peri-urban areas

5.1 Introduction

Microfinance has increasingly attracted attention from the global development community because it is considered a powerful tool in poverty alleviation strategies in developing countries (Microcredit Summit, 2004). A common argument for microfinance is that it may help keep household production stable and mitigate adverse shocks; thus it helps to prevent school dropout and reduction in spending on healthcare (Armendariz & Morduch, 2005; Dehejia & Gatti, 2002; Edmonds, 2006; Jacoby & Skoufias, 1997; Maldonado & Gonzalez-Vega, 2008; Ranjan, 2001). The effects on education and health are critical to sustainable poverty reduction since they affect the quality of human capital formation and the productivity of future generations.

But there is a debate about the impact of microfinance (Cull, Kunt, & Morduch, 2009) including its impact on education and healthcare of borrowing households. For example, if access to credit raises female economic activity it may lead to children being taken out of school to replace maternal inputs in the care of younger siblings or to work in expanded household businesses. The debate has resulted from mixed evidence on microcredit impacts. On the one hand, microcredit has positive impacts on education, for example Pitt and Khandker (1998) find girls receive more schooling if households borrow from the Grameen Bank. On the other hand, some studies find no effects or adverse effects on child education (Hazarika & Sarangi, 2008; Islam & Choe, 2009; Morduch, 1998). Likewise, in terms of health, Pitt, Khandker, Chowdhury and Millimet (2003) find higher weight-for-age and height-for-age amongst children of Grameen Bank borrowers, but Coleman (1999, 2006) finds negative impacts of microcredit on healthcare spending by households in Northeast Thailand.

One difficulty in evaluating the impact of microcredit is that borrowers and non-borrowers typically differ in both observable and unobservable characteristics. The borrowers may self-select into borrowing activities due to their better characteristics. This makes it hard to form a counterfactual of what would have happened to the borrowers in the absence of credit and clouds interpretation of any estimated treatment effects. If studies fail to correct for this self-selection problem, the estimates will give naïve and overestimated results of the impact (Coleman, 2006). One estimation approach that may better suit this problem is propensity score matching (PSM) where treatment effects are estimated by simulating a randomized experiment, matching households in the treated group with households in the control group that are as alike as possible – based on observable factors. It is then assumed that the matched households would have no systematic differences in response to the treatment, so they provide a valid counterfactual. Proponents state that PSM can replicate benchmarks from randomized experiments when used appropriately (Dehejia & Wahba, 2002).

In this chapter, a new survey, designed by the author to meet the conditions under which PSM works well, is used to examine the impact of household credit on education and healthcare spending by the poor in peri-urban areas of Ho Chi Minh City, Vietnam. In addition to matching statistically identical non-borrowers with borrowers, my estimates also control for household pre-treatment income and assets. These pre-treatment variables may be associated with unobservable factors affecting both credit participation and the outcomes of interest, so inclusion of these variables helps deal with the self-selection problem that may have biased some previous estimates of microcredit impacts.

In addition to the use of PSM, two other important features of the current analysis warrant comment. *First*, my evidence comes from a newly industrializing peri-urban area on the outskirts of a city of over seven million people. In contrast, most studies of microcredit impacts have been for rural households.[48] Poverty is becoming more urban and the poor are urbanizing more rapidly than the population as a whole (Ravallion, Chen & Sangraula, 2007). Thus, it is important that studies of microcredit expand to cover urban areas. The impacts of microcredit may differ between urban and rural areas, particularly for my outcomes of interest, since human capital is typically the most important household assets in urban areas and is rewarded more than in rural areas (Goetz & Rupasingha, 2004; Sicular et al, 2007). Also, urbanites consume less from own production and rely more on the market; so the influence of idiosyncratic shocks like illness and loss of employment may be larger in urban areas than in rural areas. Household credit can be a useful tool to fill the income gap created by the shocks; thus, in urban areas credit may be used to support consumption

[48] Previous studies in Vietnam just focused on the rural areas (e.g., Quach, Mullineux, & Murinde, 2005; Nguyen, 2008).

expenditure on healthcare, school fees and food rather than production expenses as found in rural areas (Barslund & Tarp, 2007; Johnson & Morduch, 2007).

The *second* important feature of this analysis is that it considers both formal and informal credit. Most previous studies examine the impacts of formal or program credit but do not consider effects that credit from other sources has on the outcomes of interest (Coleman, 1999, 2006; Khandker, 2005; Morduch, 1998; Pitt & Khandker, 1998). Hence, the estimated treatment effects may include both those from the program participation and also those from other credit provided by relatives, friends, neighbours and informal moneylenders. On the other hand, my survey captures all sources of credit and the results reported below compare the effects of formal and informal credit. Access to formal credit is often influenced by policy makers, but there is less leverage over informal credit, so distinguishing their separate impacts is of interest.

The remainder of the chapter is organized as follows. Section 5.2 reviews previous studies of household credit impacts on education and healthcare. Section 5.3 discusses the estimation methodology. The empirical results are reported in Section 5.4. The final section presents concluding remarks.

5.2 Previous literature

Credit may affect household demand for education and health in two ways (Armendariz & Morduch, 2005, p. 201). On the one hand, microcredit may help households earn higher income, which raises consumption and increases the demand for healthcare and children's education. On the other hand, if microcredit causes higher female employment, it then may decrease children's schooling if children have to replace mothers' input into the care of younger siblings or work in enlarged household businesses.

There is mixed evidence on these potentially opposing effects. Inadequate schooling in poor countries is often attributed to lack of access to credit since households facing adverse shocks and having insufficient access to credit may pull children out of schools to reduce household expenditure and increase labour income by increasing working hours, including child labour (Dehejia & Gatti, 2002; Edmonds, 2006; Jacoby & Skoufias, 1997; Kurosaki, 2002; Ranjan, 2001). In addition, borrowing households may take children out of school to work in family businesses (Hazarika & Sarangi, 2008) because small loans, a typical type of loan for poor households, are often associated with higher interest rates and short-term repayment conditions; the loans therefore require high returns to repay (high) interest rates to lenders. To meet these requirements, poor borrowers may reduce their costs by using their own labour, which may include child labour. For example, Beegle, Dehejia and Gatti (2004) in a study on Vietnam find households who borrowed from higher interest rate sources use more child labour.

Impacts on health and education may also interact. For example, if borrowing enables parents to provide medicines promptly once children are sick, then it may shorten sickness time and keep children at school. Healthier children may have better school performance, which helps keep children at school longer so they more productive adults. In contrast, lower school achievement and attendance are associated with child malnutrition (Glewwe, Jacoby, & King, 2000). Healthcare services such as pasteurization, health insurance, family planning and pregnant-mother care are observed to be consumed more by microfinance clients than non-clients (CGAP, 2003).

5.3 Analytical framework[49]

5.3.1 Impact evaluation problems

The most difficult part of credit impact evaluations is to separate the causal effect of credit from selection and reverse causation biases which are very common to nearly all statistical evaluations (Armendariz & Morduch, 2010). To net out the treatment effects from other factors, requires answering the question of how borrowers would have done without any credit participation (Armendariz & Morduch, 2005, 2010). This question is not easy to answer because researchers are unable to observe the virtual outcomes needed to construct such a counterfactual.

Formally, estimating the impact of credit participation is to measure the difference in the outcome between treatment and control groups, that is, $E(Y|D=1) - E(Y|D=0)$ where Y is the outcome, and D is the treatment taking value 1 if receiving treatment and 0 if otherwise. The difference in the outcome, however, may result from differences in observable characteristics, differences in unobservable characteristics, or from the treatment (credit participation). Estimates will be biased if one does not control for the differences in observable and unobservable characteristics. The differences in the observable characteristics cause "overt bias", which can be removed by controlling for observables (X_i) in

[49] Sample design and data collection were discussed in Chapter 1.

estimation models (Lee, 2005). Thus, the impact is now E(Y| D=1, Xi) – E(Y|D=0, Xi). However, the estimated impact may also include a "hidden bias" resulting from unobservable characteristics. Design-based studies such as those with a randomised selection of treatment and control groups can help in this regard because the randomization enables us to cancel out the differences in both observable and unobservable characteristics between the two groups. But in credit impact evaluation, it is very hard to conduct the randomization with human subjects due to motivation and contamination problems (Mosley, 1997).

Therefore, there are usually some problems in measuring the impact using non-experimental data because of non-random placement of credit programs and self-selection into credit participation by borrowers. The estimates of the causal effect can have selection bias if credit participation is correlated with unobserved characteristics that also affect the outcomes. For instance, households that are better motivated to invest in children's schooling may have higher demand for credit. Without an adequate measure of motivation, this omitted factor may make an observed correlation between credit and schooling seems like a causal effect.

For my sample, the non-random placement of credit borrowing is not an important issue because all the surveyed households in the sample have income per capita under VND6,000 thousand, so are eligible for preferred credit (i.e. subsidised interest and easy conditions) from government funds. Selection by informal lenders and self-selection into credit borrowing due to unobservables, however, may occur. If data on pre-treatment variables of interest are available, researchers may examine differences in these variables in order to see whether there is a positive or negative selection on unobserved characteristics, conditional on the observed characteristics. If Y^T_0 and Y^C_0 are the outcomes for treated and control groups at time 0 (before the treatment), and after controlling for the observables, $E(Y^T_0 \mid D=1, X_i) \neq E(Y^C_0 \mid D=0, X_i)$, one should suspect unobservable confounders are affecting the treatment and outcomes, i.e. there exists "hidden bias" caused by the unobservable confounders. Lee (2005, p. 125) recommends that controlling for Y_0 (together with X_i on the right hand side) may to some extent reduce the hidden bias. In my case, I do not have pre-treatment data on the variables of interest but I could use pre-treatment (baseline) income per capita as a control variable, as suggested by Mosley (1997), Heckman and Smith (1999), and McKenzie, Gibson and Stillman (2010).

$$Y_{ij,t-1} = \alpha + \beta.D_{ij,t} + \lambda.X_{ij,t} + \varepsilon_{ij,t-1} \quad (5.1)$$

where Y_{ij} is the outcome of interest of household i in ward j; D is a dummy variable representing if a household borrows (1) or not (0), X is a set of unchanged (or little changed) control variables over time (household characteristics). The coefficient β shows whether borrowers have higher or lower income per capita than non-borrowers prior to participating in the borrowing activities, conditional on their observed characteristics. If β is positive, that means a positive selection on unobserved attributes exists, borrowers tend to be richer than non-borrowers, which will lead the non-experimental estimators to overstate the impact of credit participation.

5.3.2 Methods for measuring impacts

Experimental data are not available in my case, and thus I need to employ non-experimental methods. The non-experimental methods try to construct counterfactual outcomes for borrowers as if they had not borrowed, and then compare the current outcome with the counterfactual. The existing non-experimental methods used so far in credit impact evaluations are classified as below.

5.3.2.1 Quasi-experimental methods

In the experimental method, the control group is similar to the treatment group in terms of both observed and unobserved attributes by using the randomization procedure (Bryson, Dorsett, & Purdon, 2002). In contrast, the quasi-experimental method tries to create a comparable control group by asking: "what would the treatment group have done without the treatment?" (Armendariz & Morduch, 2005, 2010). To do so, there are three approaches: matching, before-after difference estimator (BA), and difference-in-differences estimator (DD). In my case, I do not apply the BA and DD because data for those estimators are not available, hence I will only discuss the matching estimator.

- **Propensity score matching**

Matching selects non-participants who have similar observed characteristics to participants in order to generate a control group. Matched comparison and treatment groups are now similar in terms of observed characteristics (Dehejia & Wahba, 1999, 2002). The main advantage of the matching method is that one can draw on existing data sources, so it is quicker and cheaper to implement.

Nevertheless, matching does not control for unobservable characteristics that may cause selection bias, and as a result, the reliability of estimates is reduced or sensitive (Smith & Todd, 2005). The most widely used matching method is propensity score matching. Other methods of matching on each X (covariate matching) create a problem of high dimensionality which requires large datasets.

The propensity score matching (PSM) method first estimates the propensity score for each participant and non-participant on the basis of observed characteristics, and then compares mean outcome of participants with that of the matched (similar in terms of scores) non-participants. In other words, the purpose of the PSM is to select comparable non-borrowing households among all non-borrowing households to generate a control group, and then compare the outcome of the treatment and matched control groups. The crucial assumption is that amongst non-borrowers, those with the same or similar characteristics to borrowers should have the same outcomes as what the borrowers would have had without credit participation. This assumption is called unconfoundedness or conditional independence assumption (CIA) (Rosenbaum & Rubin, 1983). The underlying point of this PSM is that control and treatment units with the same propensity score have the same probability of assignment to the treatment as in randomised experiments (Dehejia & Wahba, 1999).

The PSM method may produce estimates with low bias if datasets satisfy three conditions (Dehejia & Wahba, 2002): (i) data for treatment and control groups are collected using the same questionnaire; (ii) both treatment and control groups are drawn from the same locality; and (iii) the dataset contains a rich set of variables relevant to modelling credit participation and the outcomes. The similarity of treatment and control groups in terms of observable characteristics will increase the likelihood of getting matched and reduce the bias. Since all surveyed households of the current study were poor prior to credit participation, the PSM method should produce less biased estimates than for a sample of the general households whose income per capita may be highly divergent. Heckman, Ichimura and Todd (1997) argue that a subpopulation of treated units is often of more interest than the overall population; and Dehejia (2005) emphasizes the better feasibility of the PSM method if applied to subgroups.

The PSM method allows control for potential bias such as non-placement and self-selection on observed characteristics into program participation (Dehejia, 2005; Dehejia & Wahba, 2002). However, this method still fails to control for unobservable characteristics which may create the hidden bias because the scores are calculated on the basic of observed characteristics only. Dias, Ichimura and Berg (2007) argue that if the treatment assignment and the outcome are affected by unobservables, the matching may give biased results because the method is unable to control for them. Observed characteristics may not fully capture individual motivation, ability and skills which may affect the treatment participation. Success of the PSM depends on how close the control group is to the treatment group in terms of space and time, and the two groups should have as little baseline difference as possible (Lee, 2005).

5.3.2.2 Non-experimental methods

When one is unable to randomly select a comparison (control) group, apart from the quasi-experimental methods, the non-experimental methods can be applied. These methods rely on the assumption of treatment assignment/selection based on observed characteristics.

- **OLS and Tobit models**

OLS is used to estimate the impact of credit participation with an assumption that all differences (except for the credit participation status) between borrowers and non-borrowers affecting outcomes can be captured by the regressors X_{ij} in an OLS regression, and the coefficient of interest, β, just reflects the impact of credit participation and not any omitted variable bias. The regression is as follows:

$$Y_{ij} = \alpha + \beta.D_{ij} + \gamma.X_{ij} + \varepsilon_{ij} \tag{5.2}$$

where Y_{ij} is the outcome of interest of household i in ward j; D_{ij} is a dummy representing if a household borrows (1) or does not (0); and X_{ij} is a set of control variables. For education expenditure, some households have no data on outcomes of interest, so the Tobit model will be employed; this maximum likelihood estimation method estimates the likelihood function using an additional assumption that the error terms are normally distributed. The Tobit estimator is more appropriate than the Ordinary Least Squares (OLS) because the OLS parameter estimates of limited dependent variable models are biased and inconsistent (Gujarati, 1995, p. 573; Stock & Watson, 2003, p. 328).

However, the selection into credit participation on unobserved characteristics may create a non-zero correlation between ε_{ij} and D_{ij}. Therefore, selection bias on unobservable characteristics is beyond both OLS and Tobit method's accountability. The OLS and Tobit estimates may not reflect the impact accurately.

- **Instrumental variable model**

The IV method needs good instruments which predict the participation but do not affect the outcome of the treatment. When using IV models, one should bear in mind that the tests for validity of instruments and weak instruments are very important. When instruments are valid but weak, the IV estimator may be even more biased than the OLS estimators (Murray, 2006; Stock & Yogo, 2002).

My potential instruments are household assets acquired over 24 months prior to the survey, pre-treatment income per capita, and distance to the nearest bank or credit institution. These variables may affect credit participation but not outcomes. I conducted the under-identification, over-identification and weak identification test. The tests show that my instrument candidates are weak, and hence the IV estimates may be highly upward biased. I also implemented the Hausman test, the test results accept the hypothesis that the difference between Tobit (for education expenditure) and IV Tobit estimated coefficients is not systematic. So I am able to conclude that the instruments are weak and it is not appropriate to apply IV models in my study (see Appendix 5.7 for detail of the tests). In addition, these instruments may not have valid exclusion restriction if they partly affect both the credit participation and the outcomes (education and healthcare expenditure). For instance, households having shorter distance to the nearest bank also have shorter distance to schools and healthcare centres because banks, schools and healthcare centres are typically located in community/ward centres. As a result, the distance to the closest bank, as an IV, may influence both credit participation and outcomes (education expenditure and healthcare expenditure).

5.4 Empirical results

In this section, I start with a simple test for self-selection into credit participation in Sub-section 5.4.1. OLS estimation (and Tobit for education expenditure) results are presented in Sub-section 5.4.2 to provide an initial examination of the impact of credit participation on education, healthcare and other consumption expenditure. Sub-section 5.4.3 presents PSM estimates of the impact on education and healthcare expenditure. Sub-section 5.4.4 applies a simple strategy to detect unobserved selection bias by employing the multiple treatment effect method.

5.4.1 Self-selection into credit participation

As discussed in section 5.3.1, in this subsection I conduct the test for positive selection by regressing pre-treatment income on credit participation status, conditional on household observed characteristics, as in the equation 5.1. I observe a positive selection of borrowers (positive β). The borrowers and non-borrowers are observed to be different in terms of not only observed characteristics such as age, household size, and location (Table 5.1) but also in terms of unobservable characteristics (Table 5.2). Conditional on the household head's gender, age, education, and marital status, and on household size and ward dummies, the pre-treatment income difference is VND171 thousand and is statistically significant at the 10% level. In logarithms (the last column of Table 5.2), borrowers' pre-treatment income is observed to be 7% higher than that of non-borrowers (statistically significant at the 5% level).

Income per capita prior to credit participation may capture a host of unobservable attributes (e.g. entrepreneurial ability, skills, motivation) which affect outcomes of credit participation such as education, healthcare expenditure and other consumption expenditure, and also affect the likelihood of credit participation. In other words, the hypothesis that the borrowers are self-selected in terms of the unobservable characteristics is plausible. Therefore, non-experimental estimators that fail to control for unobservables might overestimate impacts. But controlling for the initial variables such as income and assets may reduce the bias caused by the unobservable attributes (Mosley, 1997, p. 14). Indeed, Dehejia and Wahba (1999, 2002) state that PSM can be a reliable estimator if the pre-treatment earnings are controlled for.

5.4.2 OLS and Tobit estimation

To examine the impact of credit participation on expenditure (apart from observed household characteristics such as head's gender, age, education, marital status, household size, number of children and location dummies), I controlled for pre-treatment factors such as pre-treatment income and assets as proxies for unobservable characteristics which may affect the outcomes.

5.4.2.1 Credit participation impact on monthly education expenditure

Table 5.3 shows the Tobit estimates of the credit impact on education expenditure for the sub-sample of households having children aged from 6 to 18 years (official school ages in Vietnam). In the left panel (columns 1 to 4) are the results for household monthly average education expenditure, while the right panel (columns 5 to 8) has results for monthly average education spending per school-age child. The initial specification controls for household characteristics, ratio of school-aged children to household size and location dummies (columns 1 and 5). Controls for pre-treatment household income per capita and assets acquired over 24 months prior to the survey are then added (columns 2 and 6). To check the consistency of the estimates, the ratio of school-aged children is replaced with the number of school-aged children (columns 3, 4, 7 and 8). All signs of coefficients are as expected, and the estimates show a consistently positive impact of credit participation on education expenditure across the models. Controlling for household pre-treatment income and assets reduces the impacts slightly; but they remain statistically significant at the 5% level. For a Tobit model, the Tobit coefficient when multiplied by the fraction of uncensored observations gives the impact of the credit participation on the unconditional expected value of the dependent variable (Greene, 2003). This is shown as credit impact = β*(uncensored observations/total observations) in the top row of Table 5.3. Borrowing households spent an average of VND119 thousand to VND133 thousand more per month on children's education than do non-borrowing households.[50]

5.4.2.2 Credit participation impact on monthly healthcare expenditure

The OLS estimates in Table 5.4 show clearly that credit participation has a significant and positive impact on household healthcare expenditure. Controlling for household characteristics and location dummies, the borrowers spent about 86% more on healthcare than non-borrowers (columns 1 and 5).[51] Controlling further for the household pre-treatment household income per capita and assets, the impact declines slightly, but it is still highly significant (columns 2 and 6).

These results are robust to different ways of dealing with how various age-ranges affect household healthcare expenditure (columns 3 and 4). The elderly

[50] Estimated impact seems to be consistent if the whole sample is considered, and the impact is statistically significant at the 1% level.

[51] The effect is calculated as 100*[exp(β)-1]

have the strongest effect on healthcare expenditure because they are often sick, so households spend more on their healthcare. The second strongest effect is from the presence of children under six years old which is an age group with high malnutrition (Ministry of Health, Vietnam);[52] children often suffer illness e.g. diarrhoea and influenza.

5.4.2.3 Impact on other monthly household expenditures

Apart from the human capital investment, I also consider the impact of credit on daily household consumption including food and other household spending (non-food, housing expenditure, etc).[53] Credit participation positively and significantly affects the other household spending but insignificantly affects food expenditure.

5.4.3 PSM estimation

In this section, kernel (with the default bandwidth of 0.06) and radius matching (with the default radius of 0.1) PSM results of the credit impact on education and healthcare expenditure are discussed.[54] Beginning with the same sets of covariates used in the OLS and Tobit regressions; interaction terms were also used to get balancing in estimating the propensity scores.[55] The sets of controlling covariates should meet conditions of matching controlling variables discussed in Imbens (2004), Lee (2005), Rosenbaum and Rubin (1983) among others. Appendix 5.5 presents discussion on how I chose covariates in the score estimation stage.

5.4.3.1 Impact on education expenditure

My base specifications (S_1 and S_3 in Table 5.5) use the same set of covariates as used in Models 1 and 3 (Table 5.3) for the Tobit regressions to estimate the scores. Though I do not have panel data to apply the difference-in-difference matching estimator which is believed to be considerably better than cross-sectional matching estimators, inclusion of the pre-treatment household income and assets may reduce bias associated with unobservable characteristics (Imbens & Wooldridge, 2009; Mosley, 1997). The credit effects when pre-treatment income and assets are included in the matching are reported in the second (S_2) and fourth rows (S_4) of Table 5.5. The purpose of changes in model specifications between S_1 and S_3, and between S_2 and S_4 is to check the sensitivity of the effect.

[52] http://www.moh.gov.vn/homebyt/vn/portal

[53] Estimates are reported in Appendix 5.1.

[54] For discussion on implementation of various matching estimators and their advantages and disadvantages, see Appendix 5.4.

[55] By doing so I may compare the estimation results.

Figure 5.1 below shows the kernel densities of the propensity scores when pre-treatment income and assets are included alongside the other controlling variables (S_4 in Table 5.5). My matching satisfies the overlap and common support assumption (see more discussion in Appendix 5.6). The figure illustrates a substantial overlap in the distributions. The propensity scores range from 0.418 to 0.943 and from 0.174 to 0.940 for borrowers and non-borrowers, respectively,[56&57] but the means of scores are not much different (0.761 and 0.675 for borrower and non-borrower groups, respectively). The following estimation of the average treatment effect is restricted to the area of common support, where the two distributions overlap. Thus, some non-borrowers who are quite unlike the borrowers are not used in the comparison.

The estimates of the average treatment effect of credit participation on the treated (ATT) are reported in Table 5.5 for the whole sample.[58] There is little difference in results between the two matching approaches used. Matching just on household characteristics and location dummies (S_1 and S_3), the effect of credit is observed to be statistically significant at the 1% level. After including the pre-treatment income and assets (S_2 and S_4) the estimated impact of credit participation on education spending declines but is still significant at the 5% level.

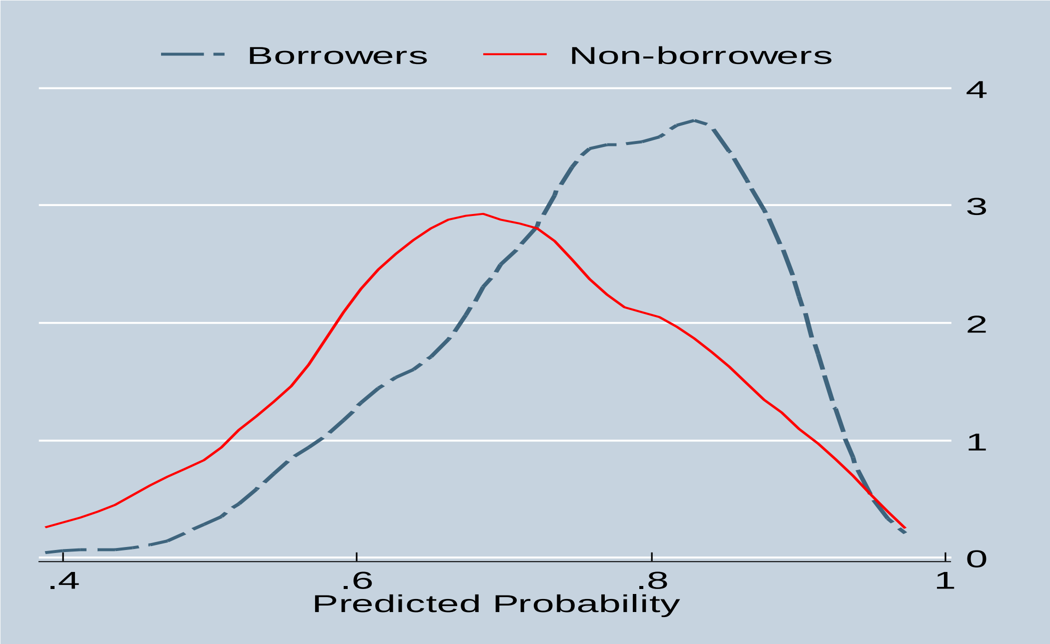
According to these PSM estimates, the borrowers on average spent about VND81 to VND99 thousand more on education per month than do their similar non-borrower counterparts. These estimates are lower than those from the Tobit model (which were about 119 to VND133 thousand, equivalent to about US$7.1 to US$7.8).

[56] Probit estimation for constructing propensity scores is reported in Appendix 5.2.

[57] Some studies suggest that the estimation should be in the range of 0.1 to 0.9, but there are 44 observations having greater scores than 0.9 (about 11% of the sample); if dropped, the estimates will be misleading (Crump et al, 2009).

[58] Estimations of the whole sample and sub-sample of households having school-age children give very similar results since PSM selects similar non-borrowers in the control group to construct the counterfactual outcomes.

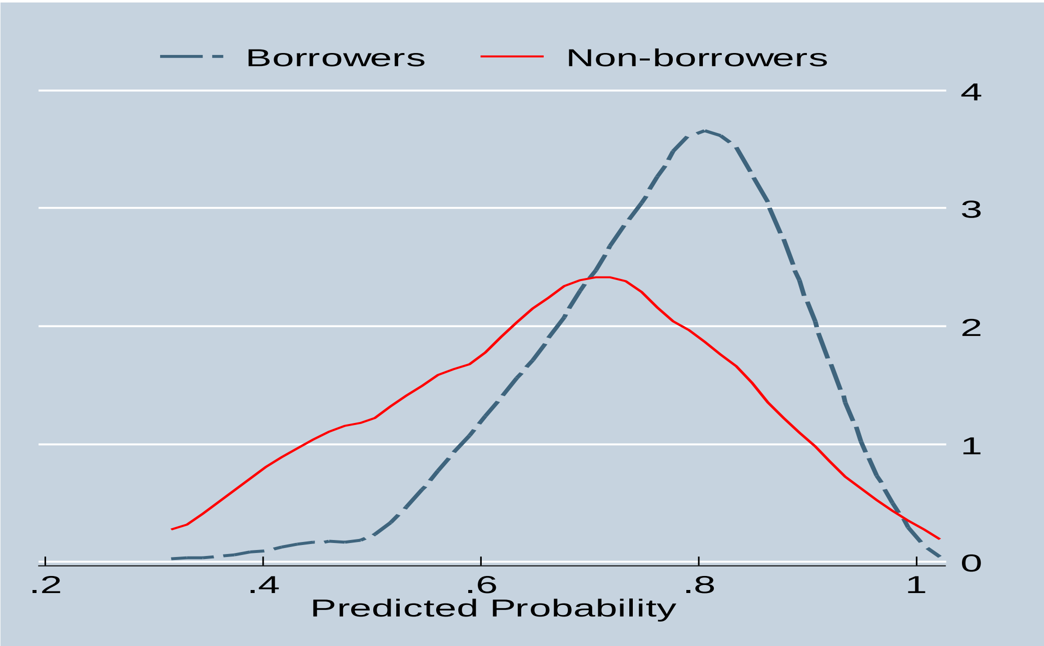
Figure 5.1: Propensity of scores for borrowers and non-borrowers to estimate ATT for education expenditure



Note: The propensity scores of control units outside the common support were cut off

5.4.3.2 Impacts on healthcare expenditure

Figure 5.2: Propensity of scores for borrowers and non-borrowers to estimate ATT for healthcare expenditure[59]



Note: The propensity scores of control units outside the common support are cut off

Figure 5.2 shows the kernel densities of the propensity scores estimated for evaluating the impact of credit on healthcare expenditure. The scores are from

[59] The sets of variables used for estimating scores to draw Figures 5.1 and 5.2 are different. Each set of the variables should affect both credit participation and outcomes (education expenditure in Figure 5.1 and healthcare expenditure in Figure 5.2). That is why two figures are slightly different.

when the pre-treatment income and assets are included alongside the other controlling variables in constructing the matches (S_4 in Table 5.6). The propensity scores range from 0.348 to 0.989 for borrowers and from 0.195 to 0.962 for non-borrowers.[60] The estimation of the average treatment effect is restricted to the common support.

The estimates of credit impact on healthcare expenditure are reported in Table 5.6. The estimates show that the effect of credit participation on healthcare expenditure is positive and statistically significant no matter which set of covariates and which matching approach are used. Borrowers spent about at least VND93 thousand more on healthcare than similar non-borrowers did.

The matching should be less biased than results from OLS or Tobit because matching compares borrowers only with similar non-borrowers. Nevertheless, the "similarity" of non-borrowers to borrowers is built on observed characteristics, so bias may still exist if unobservables affect both treatment participation and outcomes of interest. The assumption is easily violated if we are unable to control for all variables, especially the unobservables that affect both the treatment participation and outcomes (Bryson, Dorsett, & Purdon, 2002). However, since I focus only on the poor, the disparity in unobservables between borrowers and non-borrowers may not be so large. Furthermore, I also controlled for household pre-treatment income and assets which are more likely to be associated with some unobservable attributes such as motivation, entrepreneurial ability and skills. As a result, the bias may be reduced and the reliability of the matching estimates improved.

5.4.4 Multiple ordered treatment effect

In this section, multiple treatment effects are estimated to contrast the impacts of informal and formal credit on education and healthcare expenditure. An additional advantage of multiple treatment effects is that they may help to detect potential bias associated with unobservable characteristics, which estimates of binary treatment effects are unable to deal with (Lee, 2005). This usage follows from a suggestion of Lee (2005) to explore the presence of selection bias by checking whether the main scenario of treatment effect is coherent with auxiliary findings. Specifically, applying the multiple ordered treatment effects in the current context treats credit from formal sources (F) as a full treatment, and credit from informal

[60] The Probit estimation for constructing propensity scores is reported in Appendix 5.3.

sources (I) as a partial treatment.[61] When the treatment level is increased, the effect will become stronger (a good treatment). In contrast, if the treatment is reduced, then the effect will be weaker (a bad treatment). Assume that our expectation is a positive effect, but is not confirmed by multiple ordered treatment effects, then the initial causal findings (from binary treatment) are questionable and may be due to some unobserved attributes (Lee, 2005, p. 119). On the other hand, if there is no hidden bias, the treatment effect of the full treated group (F) is expected to be higher than that of the partial treated group (I), and in turn the effect of group (I) is greater than that of the non-borrower group (N), controlling for the same set of covariates X_i.

One may question that the counterfactuals of the informal and formal groups are different, so their treatment effects are not comparable. To overcome this issue, I directly compare the informal and formal credit groups, set either of them as a control group and if the estimation outcome is consistent with the multiple treatment effect, then the unobserved confounder will be confirmed.

The estimations of the multiple treatment effects using the PSM method can employ the conventional matching estimators (Rosenbaum & Rubin, 1985). In the first stage of score estimation, the multinomial Logit (or Probit) model is used (Lechner, 2001). If the treatment is logically ordered, the ordered Logit/Probit is applied instead (Imbens, 2000). Nevertheless, the multinomial or ordered Logit/Probit are quite burdensome, hence a series of binary treatment estimations may be used instead (Caliendo & Hujer, 2005; Imbens & Wooldridge, 2009; Lechner, 2001). I follow this strategy and in turn compare the formal credit group with the non-borrowing group, the informal credit group with the non-borrowing group, and the formal credit group with the informal credit group.

Estimates of the multiple treatment effects on education expenditure are reported in Table 5.7. The estimation procedure is similar to binary treatment effects in Section 5.4.2. In S_1 and S_3, household characteristics are used to construct the scores, then pre-treatment income and assets are controlled for in S_2 and S_4. The estimated impacts for informal credit are in columns 2 and 3, and the estimates for formal credit effect are in columns 4 and 5.

[61] Mean of accumulated loans *per household* is VND8,317 (about US$500) and VND15,135 thousand (about US$920) for informal and formal credit respectively, and average size *per loan* is VND5,229 thousand (about USD317) and 9,327 thousand (about USD566) for informal and formal credit respectively.

The estimates show that informal credit has no significant effect on household education expenditure. In contrast, formal credit strongly affects education expenditure. Both kernel and radius matching estimators display similar estimates that are statistically significant at the 1% level. To guard against the higher impact of formal credit on education expenditure being attributed to better household characteristics (higher pre-treatment income and assets), I included these variables in the first stage of propensity score matching.

A further step to confirm the absence of hidden bias is to directly compare impacts of formal credit (a higher level of treatment) to informal credit (a lower level of treatment). Estimates of the difference between the formal and informal credit are shown in the last column of Table 5.7. The estimates are consistent across the specifications of the matching variables. The higher credit level (treatment level) leads to a greater positive impact; suggesting that serious bias due to unobservables is not detected. Consequently, the positive treatment effect of credit on education expenditure appears to be collaborated.

Likewise, I look at the impact on healthcare spending of formal and informal credit, and the difference in impacts of formal and informal credit. The impact estimates of informal credit and formal credit on healthcare expenditure are reported in Table 5.8. The results of the difference in impacts between formal and informal credit are presented in the last column of Table 5.8. The impact of informal credit is positive but only marginally significant at the 10% level. In contrast, the impact of formal credit on healthcare is more than double the effect of informal credit, although not precisely estimated (statistically significant at the 10 percent-level).

Using multiple ordered treatment effects can either undermine (if unobserved biases are present) or enhance (if no unobserved biases) findings of the initial binary treatment effect. While the multiple treatment effect method itself is unable to overcome unobservable bias, it helps to avoid being misled in interpreting binary treatment effect estimates (Lee, 2005, p. 121). In the current case, the higher treatment level has greater positive impacts on healthcare and education expenditure, suggesting that there are no other potential factors or confounders affecting credit participation and healthcare/education expenditure. As a result, the positive treatment effects of credit on healthcare and education are confirmed.

5.5 Concluding remarks

This chapter presents estimates of the impacts of credit participation on the poor's education and healthcare expenditure in peri-urban areas of HCMC, Vietnam using a new survey designed to meet the conditions for the PSM method.

The main conclusions from the estimates are as follows: *First*, OLS and Tobit estimates show that credit participation has positive and significant effects on household education and healthcare spending but not on food expenditure. As expected, my estimation results indicate that for the poor in peri-urban areas of Vietnam, the impact on food expenditure is not significant, which contrasts to Quach, Mullineux and Murinde (2005) who found that credit participation has positive and significant impact on per capita food expenditure in rural areas of Vietnam. Furthermore, food expenditure is a good proxy for household consumption and I find that food expenditure is much smaller impacted than spending on education and healthcare (human capital formation); therefore, facilitating access to credit for the poor is very important to support investments that can sustainably eliminate poverty.

Second, the PSM estimates of the average treatment effect show that borrowers spent more on education and healthcare than their similar non-borrowers. Credit participation has highly positive and significant effects on the poor's healthcare and education spending in the peri-urban areas.

The PSM estimates are considerably lower and less biased than those of the OLS because PSM compares borrowers with similar non-borrowers. I focus on the poor so that the disparity between treatment and control units is little. I also controlled for the pre-treatment income which is more likely to be associated with some main unobservable attributes such as motivation, entrepreneurial ability and skills. Therefore, my estimation strategy is likely to reduce the bias and improve the reliability of the matching estimates. Furthermore, all the treated units are within the common support and no treated units are dropped when estimating the ATT effect, thus my estimates may not be misleading.

Third, this study employs the multiple treatment effects and shows that only formal credit impacted positively and significantly on household education and healthcare spending. The ordering of results suggests that no other important unobserved factors substantially affected credit participation and the outcomes;

hence the reported effects of household credit on education and healthcare spending may be robust.

TABLES

Table 5.1: Descriptive statistics and *t*-values for equal means by borrowing status

Variables	Borrowers		Non-borrowers		*t*-value
	Mean	Std.Dev	Mean	Std.Dev	
Pre-treatment or fixed variables					
Head's gender (male=1)	0.507	0.501	0.505	0.502	0.03
Head education (year)	4.911	3.35	4.664	3.76	0.60
Married (yes=1)	0.648	0.478	0.607	0.491	0.74
Head's age	52.901	13.97	59.467	15.46	3.87**
Household size	5.191	2.343	4.523	2.597	2.34*
Children below 6 years old (yes=1)	0.309	0.463	0.178	0.384	2.89**
Children from 6 to 18 years old	1.118	1.024	0.869	1.100	2.05*
Persons from 18 to 60 years old	3.230	1.694	2.692	1.793	2.71**
Older-than-60 persons (yes=1)	0.352	0.478	0.533	0.352	3.25**
Distance to nearest bank (Km)	2.226	2.098	1.804	1.900	1.93+
Distance to nearest market (Km)	1.409	1.032	1.085	0.872	3.10**
Have a phone (yes=1)	0.809	0.394	0.644	0.481	3.18**
Internet/newspapers (yes=1)	0.053	0.224	0.037	0.191	0.68
Have a TV and radio (yes=1)	0.944	0.230	0.925	0.264	0.66
Durable and fixed assets acquired over 24 months prior to the survey	849,924	821,335	786,097	795,593	0.71
Pre-treatment income per capita	3,592	814	3,505	925	0.86
Post-treatment variables					
Total monthly food expenditure	2,122.6	1,247	1,874.3	1,355	1.66+
Total monthly non-food expenditure[(a)]	1,525.3	1,612	1,206.2	1,309	2.04*
Total monthly education expenditure	269.10	332	155.25	239	3.80**
Total monthly education expenditure[(b)]	324.67	347	234.51	267	2.21*
Total monthly health care expenditure	299.67	582	220.84	552	1.25
Total monthly housing expenditure[(c)]	199.39	274	145.64	163	2.41*
Monthly expenditure (food, nonfood, education, healthcare, housing)	4,416.1	2738	3,602.2	2,597	2.75**
Monthly expenditure per capita	918.18	589	878.41	533	0.60

Notes: t-value statistically significant at 10% (+), 5% (*), and 1% (**); assets, income, and expenditures are in VND 1,000. [(a)]This includes daily and yearly non-food expenditure excluding health, education and housing expenditure; [(b)]for a sub-sample of households having children below 18 years old; [(c)]this includes garbage disposal, electricity bill, drinking and water bill, housing maintenance expenses. Exchange rate USD/VND=16,481 in 2008.

Table 5.2: Testing for positive selection into credit participation (OLS estimation)

Explanatory variables	No control	Controls(1)	Controls(2)
Credit participation (yes=1)	86.86	170.72	0.068
	(0.86)	(1.81)+	(2.05)*
Head's gender (male=1)		44.39	0.017
		(0.45)	(0.53)
Household head's age		40.37	0.013
		(1.97)*	(1.89)+
Head's age squared		-0.36	-0.000
		(2.00)*	(1.90)+
Head's education (years of schooling)		0.50	0.001
		(0.04)	(0.17)
Head's marital status (married=1)		65.77	0.016
		(0.58)	(0.42)
Household size in logarithm		-180.11	-0.065
		(2.16)*	(2.45)*
Long Truong ward		-918.24	-0.226
		(7.20)**	(4.98)**
Long Phuoc ward		-238.79	-0.020
		(1.87)+	(0.44)
Phuoc Binh ward		-609.26	-0.119
		(4.40)**	(2.44)*
Constant	3,505.50	3,034.35	7.918
	(39.26)**	(5.08)**	(38.24)**
R-squared	0.002	0.202	0.160
Observations	411	411	411

*Notes: Robust t statistics in parentheses; +significant at 10%; *significant at 5%; **significant at 1%; Dependent variable is the pre-treatment income per capita (in VND1,000) in Control and Controls(1), and in natural logarithm in Controls(2). The ward TNPA is set as a reference dummy for other wards.*

Table 5.3: Tobit estimates of the impact on education expenditure for a sub-sample of households having children from 6 to 18 years old

Explanatory variables	Model specification							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit impact	127.43	119.22	132.66	121.02	87.24	79.23	92.93	83.92
Credit participation	140.34 (2.61)**	131.29 (2.45)*	146.09 (2.77)**	133.28 (2.55)*	96.07 (2.48)*	87.25 (2.27)*	102.34 (2.63)**	92.42 (2.39)*
Head's gender	76.31 (1.57)	71.30 (1.48)	64.39 (1.34)	58.50 (1.24)	55.57 (1.59)	51.74 (1.49)	54.61 (1.55)	50.57 (1.45)
Head's age	1.94 (1.07)	1.99 (1.10)	1.74 (1.03)	1.46 (0.88)	-1.21 (0.92)	-1.14 (0.88)	0.85 (0.68)	0.69 (0.56)
Head's education	18.77 (2.70)**	17.14 (2.48)*	21.37 (3.11)**	19.53 (2.87)**	12.32 (2.46)*	11.12 (2.24)*	11.71 (2.31)*	10.51 (2.09)*
Marital status (married=1)	31.71 (0.55)	25.78 (0.45)	18.17 (0.32)	2.94 (0.05)	-19.66 (0.47)	-26.22 (0.63)	24.83 (0.60)	13.01 (0.32)
School child ratio	59.51 (0.39)	129.61 (0.83)			-501.42 (4.52)**	-447.92 (4.00)**		
Pre-treatment income in log		34.95 (0.43)		55.70 (0.70)		63.28 (1.07)		64.31 (1.08)
Pre-treatment assets in log		39.94 (2.24)*		46.69 (2.69)**		26.82 (2.09)*		28.95 (2.25)*
Children 6 to 18 years old			72.41 (2.93)**	84.81 (3.43)**			-72.31 (3.97)**	-63.75 (3.48)**
Constant	-79.01 (0.48)	-879.6 (1.22)	-160.73 (1.17)	-1,186 (1.71)+	329.30 (2.78)**	-535.02 (1.02)	136.00 (1.34)	-742.89 (1.44)
Wald χ^2	49.83	55.03	58.16	65.86	57.61	63.17	53.24	59.52
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Uncensored	237	237	237	237	237	237	237	237
Censored	24	24	24	24	24	24	24	24
Observations	261	261	261	261	261	261	261	261

*Notes: Absolute t statistics in parentheses; + significant at 10%; * significant at 5%; ** significant at 1%; Dependent variable for Models 1-4 are monthly average education expenditure in VND1,000; for Models 5-8 are monthly average education expenditure per child. Credit impact=β*(uncensored/total observations). All model specifications were controlled for ward dummies.*

Table 5.4: OLS estimates of the impact on healthcare expenditure in logarithm

Explanatory variables	Model specification					
	(1)	(2)	(3)	(4)	(5)	(6)
Credit participation (yes=1)	0.621	0.548	0.658	0.595	0.621	0.548
	(3.30)**	(3.00)**	(3.52)**	(3.30)**	(3.30)**	(3.00)**
Head's gender (male=1)	0.202	0.210	0.208	0.211	0.202	0.210
	(1.18)	(1.24)	(1.21)	(1.24)	(1.18)	(1.24)
Head's education (years)	0.065	0.054	0.060	0.051	0.065	0.054
	(2.67)**	(2.23)*	(2.43)*	(2.09)*	(2.67)**	(2.23)*
Head's marital status (married =1)	-0.305	-0.356	-0.181	-0.244	-0.305	-0.356
	(1.48)	(1.75)+	(0.93)	(1.27)	(1.48)	(1.75)+
Household head's age	0.009	0.008			0.009	0.008
	(1.65)+	(1.60)			(1.65)+	(1.60)
Household size in logarithm	0.761	0.727			-0.239	-0.273
	(3.98)**	(3.86)**			(1.25)	(1.45)
Child below 6 years old (yes =1)			0.300	0.229		
			(2.15)*	(1.67)+		
Children from 6 to 18 years old			-0.005	0.045		
			(0.08)	(0.73)		
Person from 18 to 60 years old			0.201	0.183		
			(4.47)**	(4.25)**		
Older than 60 (yes =1)			0.513	0.510		
			(3.16)**	(3.25)**		
Pre-treatment income in logarithm		0.797		0.665		0.797
		(2.71)**		(2.23)*		(2.71)**
Pre-treatment assets in logarithm		0.187		0.194		0.187
		(3.32)**		(3.44)**		(3.32)**
Constant	1.646	-7.067	2.327	-5.466	1.646	-7.067
	(3.69)**	(2.86)**	(7.18)**	(2.19)*	(3.69)**	(2.86)**
Observations	411	411	411	411	411	411
R-squared	0.19	0.23	0.20	0.24	0.11	0.16
F_value	7.65	9.22	7.83	8.46	4.04	6.22
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*Notes: Robust t statistics in parentheses; + significant at 10%; * significant at 5%; ** significant at 1%; Dependent variable is in natural logarithm form; models 1-4 are for monthly average healthcare expenditure (in log); models 5 and 6 are for monthly average healthcare expenditure per capita (in log) to check the economy of scale. In models 3 and 4, I dropped head's age from the models because it is highly correlated with the dummy of person older than 60 years old. All model specifications were controlled for ward dummies.*

Table 5.5: The average treatment effect on monthly average education expenditure in VND1,000 using matching estimators with whole sample

Control variables in the propensity score estimation	Treated/ controls	Kernel matching	Radius matching
Head's gender, head's age, head's education, marital status, school-aged child ratio, and ward dummies (S_1)	304/107	92.696 (31.967)**	98.696 (32.393)**
S_2=S_1 *plus* initial income in log, initial assets in logarithm	304/101	85.020 (34.027)*	93.022 (31.506)**
Head's gender, head's age, head's education, marital status, number of children from 6 to 18, and ward dummies (S_3)	304/107	87.447 (33.875)**	93.179 (34.182)**
S_4=S_3 *plus* initial income in log, initial assets in logarithm	304/101	81.232 (34.621)*	86.861 (34.448)*

Notes: Bootstrapped standard errors in parentheses with 1,000 repetitions, statistically significant at 10% (+); 5%(*); 1%(**). Only few households (10 households) have more than or equal 4 children aged 6 to 18 years old, to get balanced easier I group them into households having 4 kids. S_i are model specifications.

Table 5.6: The average treatment effect on monthly average healthcare expenditure in VND1,000 using matching estimators

Control variables in the propensity score estimation	Treated/ controls	Kernel matching	Radius matching
Specification 1 (S_1)	304/101	112.277 (48.711)*	111.267 (49.422)*
S_2=S_1 *plus* initial income in log, initial assets in logarithm	304/97	93.082 (55.382)+	94.016 (56.441)+
Specification 3 (S_3)	304/107	122.047 (46.442)**	131.161 (44.413)**
S_4 =S_3 *plus* initial income in logarithm, initial assets in log	304/102	108.313 (50.301)*	112.895 (48.612)*

Notes: Bootstrapped standard errors in parentheses with 1000 repetitions, statistically significant at 10% (+); 5%(*); and 1%(**).
*S_1: Head's gender, head's age, head's education, marital status, household size in log, head's age*gender, ward dummies*
*S_3: Head's gender, head's education, marital status, dummy of child below 6, number of children from 6 to 18 years old, persons from 18 to 60 years old, dummy of older than 60 years old, head's age*education, and ward dummies.*

Table 5.7: The average treatment effect on monthly average education expenditure in VND1,000 using matching estimators with whole sample

Control variables in the propensity score estimation	Informal credit vs. Non-borrowers		Formal credit vs. Non-borrowers		Formal vs. Informal
	ATTK	ATTR	ATTK	ATTR	ATTR
Specification 1 (S_1)	35.283 (38.173)	26.968 (37.641)	152.813 (47.642)**	159.717 (46.162)**	111.607 (44.662)*
Specification 2 (S_2)	10.963 (40.052)	13.056 (39.539)	148.027 (46.321)**	146.784 (48.596)**	117.417 (48.373)*
Specification 3 (S_3)	33.991 (37.867)	24.652 (36.579)	144.884 (46.097)**	159.113 (44.351)**	108.720 (42.935)*
Specification 4 (S_4)	7.750 (39.834)	13.440 (38.605)	145.492 (45.875)**	148.440 (48.368)**	118.657 (50.221)*

Notes: Bootstrapped standard errors in parentheses with 1,000 replications, statistically significant at 10% (+); 5%(*); 1%(**).

*S_1: Head's gender, head's age, head's education, marital status, ward dummies, school-aged child ratio, and head's age*head's gender.*

*S_2: Head's gender, head's age, head's education, marital status, ward dummies, school-aged child ratio, head's age*head's education, initial income in logarithm, initial assets in logarithm.*

*S_3: Head's gender, head's age, head's education, marital status, ward dummies, number of children aged 6 to 18 years old, and head's age*head's gender.*

*S_4: Head's gender, head's age, head's education, marital status, ward dummies, number of children aged 6 to 18 years old, head's age*education, initial income in logarithm, initial assets in logarithm.*

Table 5.8: Average treatment effect on the monthly average healthcare expenditure in VND1,000 using matching estimators

Control variables in propensity score estimation	Informal credit vs. Non-borrowers		Formal credit vs. Non-borrowers		Formal vs. Informal
	ATTK	ATTR	ATTK	ATTR	ATTR
Specification 1 (S_1)	77.197 (45.833)+	77.037 (41.612)+	192.648 (95.163)*	198.287 (98.337)*	175.762 (85.766)*
S_2=S_1 *plus* initial income in log, initial assets in log	65.709 (43.060)	68.638 (40.846)+	165.153 (96.364)+	183.121 (92.470)*	178.730 (92.515)+
Specification 3 (S_3)	59.844 (45.626)	71.473 (42.105)+	200.227 (97.934)*	198.616 (97.505)*	162.392 (92.509)+
S_4=S_3 *plus* initial income in log, initial assets in log	60.404 (44.646)	66.845 (44.254)	195.088 (97.652)*	194.632 (96.055)*	161.437 (97.067)+

Notes: Bootstrapped standard errors in parentheses with 1,000 replications, statistically significant at 10% (+); 5% (*); 1% (**). In the last column of S1 and S4, the interactions are dropped to get balanced in the estimation of propensity scores.

*S_1: Head's gender, head's education, marital status, head's age, household size in logarithm, ward dummies, head's age*gender.*

*S_3: Head's gender, head's education, marital status, dummy of child below 6 years old, number of children aged 6 to 18 years old, number of persons aged 18 to 60 years old, dummy of older than 60 years old, ward dummies, marital status*head's gender.*

APPENDICES

Appendix 5.1: OLS estimates of the impact of credit on food and other household expenditure

Explanatory Variables	Model specification			
	(1)	(2)	(3)	(4)
Credit participation	0.085	0.061	0.245	0.204
	(1.35)	(1.02)	(2.77)**	(2.39)*
Head's gender (male=1)	0.034	0.039	-0.098	-0.089
	(0.56)	(0.66)	(1.08)	(0.98)
Household head's age	0.002	0.002	0.004	0.003
	(0.99)	(0.88)	(1.33)	(1.14)
Head's education (years)	0.017	0.013	0.042	0.034
	(2.22)*	(1.76)+	(3.23)**	(2.75)**
Head's marital status	0.158	0.138	0.120	0.085
(married=1)	(2.31)*	(2.07)*	(1.24)	(0.91)
Household size in log	0.576	0.556	0.759	0.723
	(7.59)**	(7.54)**	(7.62)**	(7.49)**
Pre-treatment income		0.243		0.392
per capita in logarithm		(2.42)*		(2.72)**
Pre-treatment		0.079		0.137
assets in logarithm		(2.74)**		(5.86)**
Constant	6.168	3.264	5.519	0.718
	(35.64)**	(3.75)**	(21.60)**	(0.56)
F-value	16.73	16.78	10.98	14.10
Prob>F (all coefficients=0)	0.0000	0.0000	0.0000	0.0000
R-squared	0.35	0.39	0.30	0.37
Observations	411	411	411	411

*Robust t statistics in parentheses; + significant at 10%; * significant at 5%; ** significant at 1%; Dependent variable is in natural logarithm form; models 1 and 2 are for (monthly average) food expenditure (in log); models 3 and 4 are for (monthly average) other household expenditure. All model specifications were controlled for ward dummies.*

Appendix 5.2: Probit estimation for constructing the propensity scores to estimate impacts on education expenditure for the whole sample

Control variables	Model specification			
	(1)	(2)	(3)	(4)
Head's gender (male=1)	-0.0910	-0.0926	-0.1002	-0.1051
	(0.55)	(0.55)	(0.60)	(0.63)
Household head's age	-0.0165	-0.0157	-0.0175	-0.0170
	(3.14)**	(2.94)**	(3.44)**	(3.29)**
Head's education (years)	0.0151	0.0132	0.0162	0.0143
	(0.67)	(0.58)	(0.71)	(0.62)
Head's marital status (married=1)	-0.0767	-0.1038	-0.0960	-0.1270
	(0.44)	(0.59)	(0.55)	(0.71)
School child ratio	0.5207	0.6705		
	(1.34)	(1.70)+		
Children from 6 to 18			0.1105	0.1373
			(1.62)	(1.98)*
Pre-treatment income in log		0.5527		0.5593
		(1.90)+		(1.92)+
Pre-treatment assets in log		0.0627		0.0653
		(1.20)		(1.25)
Long Truong Ward	0.5473	0.6253	0.5404	0.6166
	(2.78)**	(2.91)**	(2.75)**	(2.86)**
Long Phuoc Ward	0.4852	0.4820	0.4761	0.4704
	(2.49)*	(2.44)*	(2.44)*	(2.39)*
Phuoc Binh Ward	0.2571	0.2725	0.2191	0.2242
	(1.23)	(1.23)	(1.04)	(1.01)
Constant	1.1461	-4.2521	1.2127	-4.2458
	(2.86)**	(1.68)+	(3.19)**	(1.68)+
LR χ^2	26.86	32.29	27.70	33.34
Prob > χ^2	0.000	0.000	0.000	0.000
Observations	411	411	411	411

*Notes: Absolute value of z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; among 411 households, there are 304 borrowing households and 107 non-borrowing households.*

Appendix 5.3: Probit estimation for constructing the propensity scores to estimate impacts on health care expenditure

Control variables	Model specification (1)	(2)	(3)	(4)
Head's gender (male=1)	-0.8468	-0.7924	-0.0963	-0.1096
	(1.50)	(1.40)	(0.57)	(0.64)
Head's age (year)	-0.0312	-0.0302		
	(3.98)**	(3.83)**		
Head's education (years)	0.0112	0.0099	0.0622	0.0581
	(0.48)	(0.42)	(0.96)	(0.90)
Head's marital status (married=1)	-0.3759	-0.3876	-0.1372	-0.1556
	(1.93)+	(1.97)*	(0.77)	(0.87)
Household size in logarithm	0.6680	0.6957		
	(4.28)**	(4.37)**		
Child below 6 years old (yes=1)			0.3426	0.3146
			(2.02)*	(1.84)+
Children aged 6 to 18			0.1194	0.1426
			(1.74)+	(2.05)*
Persons aged 18 to 60			0.0967	0.0977
			(2.06)*	(2.05)*
Older than 60 person (yes=1)			-0.3832	-0.3779
			(2.06)*	(2.03)*
Pre-treatment income in logarithm		0.6096		0.5950
		(2.04)*		(2.02)*
Pre-treatment assets in logarithm		0.0249		0.0334
		(0.46)		(0.64)
Head's age*gender	0.0143	0.0130		
	(1.42)	(1.29)		
Head's age*education			-0.0007	-0.0007
			(0.64)	(0.60)
Long Truong Ward	0.4348	0.5547	0.5245	0.6387
	(2.16)*	(2.52)*	(2.60)**	(2.91)**
Long Phuoc Ward	0.4086	0.4100	0.5036	0.5049
	(2.05)*	(2.04)*	(2.56)*	(2.54)*
Phuoc Binh Ward	0.0366	0.0837	0.1223	0.1665
	(0.17)	(0.37)	(0.55)	(0.71)
Constant	1.3743	-4.0387	0.0202	-5.3013
	(2.54)*	(1.56)	(0.08)	(2.11)*
LR χ^2	46.45	51.25	36.99	41.81
Prob > χ^2	0.000	0.000	0.000	0.000
Observations	411	411	411	411

*Notes: Absolute value of z statistics in parentheses, + Significant at 10%; * significant at 5%; ** significant at 1%; among 411 households, there are 304 borrowing households and 107 non-borrowing households.*

Appendix 5.4: Implementation of propensity score matching[62]

The procedure of propensity score matching (PSM) estimation consists of two stages. In the first stage, probit (or logit) is used to estimate the propensity score (pscore) or probability of receiving treatment conditioning on control variables, and then stratifies individuals or households into blocks according to their scores. In the second stage, the estimated propensity scores will then be used together with various average treatment effect estimators to obtain estimates of the average treatment effect on the treated (ATT). Each matching estimator and its advantages and disadvantages is discussed below.

- **Nearest neighbour matching (ATTND/ATTNW)**

For this matching method, one observation, that is closest to the treated observation in terms of the propensity score, from the control group is selected as a matching partner for a treated observation. The ATT is computed by averaging over the unit-level treatment effects of the treated. If there are multiple nearest neighbours (controls) that have the same propensity score, the average outcome of those controls is used. Bad matching is a drawback of this matching method because the nearest control unit(s) can be very far, in terms of the score, from the treated observation.

- **Stratification matching (ATTS)**

The ATTS estimator first estimates difference in average outcomes of treated and controls within the same block or interval for which the score has found all the control variables to be balanced. Then the ATT for the whole sample is computed using a weighted average of the block-specific treatment effects. The weight for each block is assigned by the corresponding fraction of treated units and the number of blocks. This approach is also called interval matching, blocking or sub-classification (Rosenbaum & Rubin, 1984). The main drawback of stratification matching is that the closest control units to a treated unit may come from a neighbouring block, but those units are not used to match with the treated unit, while farther control units in the same block with the treated unit are used to match.

- **Kernel weighted matching (ATTK)**

The ATTK is computed averaging over the unit-level treatment effects of the treated where the outcome of control unit(s) matched to a treated unit is obtained

[62] This section is heavily drawn from StataCorp (2009).

as the kernel-weighted average of control unit outcomes. The ATTK uses weighted averages of all observations in the control group to construct the counterfactual outcome. The weights assigned to each unit in the control group depend on distance to the treated unit. The closer the distance, the higher weight will be assigned to the control unit. In other words, the weights are inversely proportional to the distance between propensity scores of the treated and a control unit. One advantage of the kernel matching is the lower variance (more efficiency) than that of nearest neighbour matching because more information from all or nearly all control units is used. The disadvantage of this approach is bad matching (Caliendo & Kopeinig, 2008, p. 43) because few or many far-distance control units are used to match with one treated unit.

- **Radius matching (ATTR)**

The ATTR estimate is computed by averaging over the unit-level treatment effects of the treated where control unit(s) within a pre-defined radius of propensity scores (for example, 0.1) is/are matched to a treated unit. If there are more than one control unit within a radius, the average outcome of those control units is used. This approach can avoid the bad matches found in the nearest neighbour matching and can overcomes the drawback of stratification matching, so the quality of matching rises (Caliendo & Kopeinig, 2008, p. 42). In theory, the smaller the radius, the better the quality matching becomes since matched control units and the treated unit have close scores. Radius matching, however, uses those treated units that have control matches within a radius, so if the radius is very small, many treated units are not matched and hence dropped. Therefore, the ATT by the radius matching estimator is no longer representative of the population of the treated units (Becker & Ichino, 2002; Smith & Todd, 2005).

Caliendo and Kopeinig (2008, p. 44) summarize trade-offs between bias and efficiency (low variance) for the matching estimators. No method outweighs, so choosing methods depends on the data structure at hand (Zhao, 2003). According to Zhao, the key data requirement for the PSM is that at each propensity score value or small score interval, the number of both treated and control observations is large enough to avoid the treated unit dropouts due to being not matched. In addition, if there is/are matches within a smaller (score) radius, the quality of matching will be improved, and matching estimates will be less biased.

In the empirical studies, ATTK and ATTR are more commonly employed because the possibility of more control units used is higher for ATTK and ATTR relative to the other matching estimators, so they are more efficient.

Appendix 5.5: Choice of covariates for the propensity score estimation

In the PSM method, choosing covariates is important because they affect the estimation outcomes. According to Lee (2005, p. 44), chosen covariate X_i must be pre-treatment and affect both outcome (Y) and the treatment (D – credit participation). In addition, to avoid the causality bias, X_i should not be affected by D, hence post-treatment covariates should not be controlled for because they will remove part (or all) of the effect of D on Y.

The unconfoundedness assumption or conditional independence assumption (CIA) (Rosenbaum & Rubin, 1983) implies that the observable control covariates should not be affected by treatment, and the outcomes of interest are independent of treatment assignment. Thus, included variables should either be fixed over time or be measured before the treatment intervention (Caliendo & Kopienig 2008, p. 38). The pre-treatment measured variables also must not be affected by anticipation of the treatment participation (Imbens, 2004). For example, if households know they will receive credit, this may lead to higher consumption even before the household was lent the money.

Furthermore, variables should be excluded if they are either unrelated to the outcome or not proper covariates of the treatment participation decision model (Bryson et at, 2002; Rubin & Thomas, 1996). A variable that affects only credit participation but not treatment outcome is not necessary to control for because the outcome of interest is not affected by this variable. On the other hand, if a variable affects only the outcome but not the treatment participation, one should not control for since the variable will not make any significant differences between the treatment and control groups. Consequently, only variables that influence simultaneously the participation decision and the outcome should be included in the score estimation stage (Bryson, Dorsett, & Purdon, 2002, p. 24).

Finally, Dehejia and Wahba (1999) and Heckman, Ichimura and Todd (1997) state that exclusion of important variables could seriously increase bias in estimates. But a covariate is not, or only weakly, correlated with outcomes and the treatment may reduce precision of estimates (Imbens, 2004, p. 23). In the presence of uncertainty, however, it is better to include too many rather than too few covariates (Bryson, Dorsett, & Purdon, 2002, p. 25). Furthermore, (Dehejia and Wahba (1999) suggest starting with the covariates linearly and checking whether the balancing of covariates within each stratum is obtained, and then test for statistical significance of differences in the distribution of covariates. As the balance is obtained, the specification is accepted. Otherwise, one should change potential covariates into higher-order terms and interactions until the balancing is satisfied.

Appendix 5.6: The common support and overlap

The second assumption of PSM is the common support. Only a subset of the comparison group that is comparable to the treatment group will be used, therefore, it is necessary to check the overlap and the common support between the treatment and control groups. Lechner (2001) suggests inspecting the density distribution of propensity scores to check the overlap and common support in order to see whether comparability between the treatment and control groups is sizeable. So, what happens if the overlap is limited?

Imbens (2004, p. 24) points out how the PSM methods handle the lack of overlap. Accordingly, the probability or score receives value from 0 to 1; the observations with probabilities close to one will receive high weights, leading to an increase in variance of the average treatment effect estimator. As a result, Imbens (2004) states that the PSM is designed to better cope with limited overlap in the covariate distributions than parametric regression models because adding control observations of outliers (scores will be near 0 or 1) in a parametric regression approach will lead to substantial changes in estimated coefficients.

What happens if the assumption of the common support is violated? If treated and control observations fall outside of the common support, they need to be dropped. If the number of outside-common support observations of treatment group is large, estimate of the within-common support observations may be misrepresentative and misleading (Caliendo & Kopeinig, 2008; Imbens, 2004). Therefore, ignoring the common support problem or estimating subpopulation within the common support may give misleading estimates and inferences (Lechner, 2001).

Furthermore, the lack of overlap in covariate distributions between control and treatment groups could lead to imprecise estimates and could cause the estimators to be sensitive to choice of specification (Crump, Hotz, Imbens, &

Mitnik, 2009). The evaluators often use a strategy of trimming the sample to address the limited overlap. Crump et al (2009) suggest a simple rule of thumb to discard all units of both control and treatment groups which have an estimated propensity score outside the range [0.1, 0.9]; these authors believe that the precision gain from the approach is substantial with most of the gain captured. This is because (i) using Probit and Logit models to estimate the scores will give more different results when the propensity scores are close to 1 or 0; (ii) for units with scores close to 1 or 0, the weights could be large so these units may considerably affect the estimates of treatment effects, and hence the estimates become imprecise (Imbens & Wooldridge, 2009, p. 35). However, Crump et al (2009) also warn that potentially some external validity is lost by changing the focus to average treatment effects for a subset in the range [0.1, 0.9] of the original sample if the dropout observations significantly affect the estimated result when a large number of observations is discarded; the estimates could be misleading even if the strategy of estimation improves the lack of overlap.

Appendix 5.7: Tests for weak instruments

In this appendix, tests for instrumental variable (IV) are presented in which tests for weak instruments are emphasized. Three groups of potential instruments are: pre-treatment income (in log) and assets (in log); distance to the nearest bank within each ward; and a combination of all these instruments. So, three models with three IV groups will be run separately.

Three strategies to detect the weak instruments are utilised. The *first strategy* is to check covariance correlations between the endogenous variable (credit participation) and the potential instruments (see Appendix 5.7 Table 1):

Appendix 5.7 Table 1: Pairwise correlations between credit participation and potential instruments

Pre-treatment income in log	Pre-treatment assets in log	Distance to nearest bank			
		TNPA ward	PB ward	LT ward	LP ward
0.0785	0.0662	-0.1182	-0.0717	0.1023	0.0801

This table shows low gross correlation coefficients implying considerable efficiency loss when using the IV model compared to the conventional models (OLS, Tobit) (Angrist, Imbens, & Rubin, 1996; Belzil, 2007; Murray, 2006; Stock & Yogo, 2002). The correlations in this table, however, are not so low to suspect the weak instrument problems. Some coefficients are above 0.10, and the lowest is 0.0662. This prompts more sophisticated tests to confirm weak instruments.

The *second strategy* is to use the Hausman test for Tobit models of education expenditure (education expenditure is restricted to a sub-sample of households having children aged 6 to 18). Results of the tests are presented in Appendix 5.7 Tables 2 for the three groups of instruments. In the first stage, Probit model is used to predict probability of credit participation (*yhat*) and its residuals (*resid*). In the second stage, either the *yhat* or a combination of *resid* and credit participation variable is plugged in Tobit model for education expenditure.[63] The Hausman test then is applied to test endogeneity of credit participation. The Hausman test results show that the null hypothesis (difference in coefficients of the conventional Tobit and two-stage Tobit model is not systematic) is accepted for all three models (the last row of Appendix 5.7 Table 2). Consequently, the instruments are weak, and hence IV models are inappropriate in my case.

Furthermore, when the normal distribution assumption of dependent variable in the first stage is ignored, IVTOBIT model with joint estimation (two equations are simultaneously estimated) may be applied. The Wald test results for exogeneity of credit participation are presented in Appendix 5.7 Table 3. For a group of instruments of pre-treatment income per capita and pre-treatment assets, the test reject the hypothesis (exogeneity of credit participation) at the 10% level, but the first stage F-statistic is very low (only F-statistic=2.87, much smaller than 10). This casts doubt on the validity of these instruments, and instruments are weak. For instrument of distance to nearest bank within each ward and a combination of all instruments, the test accepts the hypotheses (see columns 2 and 3 in Appendix 5.7 Table 3). Indeed, the estimated coefficient of credit participation is very imprecise and seriously inconsistent, and this confirms that the instruments are weak as indicated in Angrist et al (1996) and Belzil (2007).

The *third strategy* is to apply the approach by Stock and Yogo (2005) to test weak instruments, and the Hansen J Statistic to test validity of instruments (over-identification test) of linear instrumental variable models of healthcare expenditure. Further, due to possible weak instruments, Limited Information Maximum Likelihood (LIML) estimator may be less of bias problem and performs better than 2SLS estimator (Staiger & Stock, 1997; Stock, 2010). In addition, since a sample of 411 households may be small, the robust LIML IV

[63] Both approaches provide the same Hausman test results.

estimator for small sample is employed (*ivreg2* command in Stata® with options of "*small*" along with "*liml, robust"*).

Results of the tests are presented in columns 1, 2 and 3 in Appendix 5.7 Tables 4 for the three groups of instruments. The Hansen J Statistic for over-identification test for the three models accepts the hypothesis of over-identification for all the three models. However, results of weak identification test (Kleibergen-Paap rank Wald F statistic) are always much lower than Stock-Yogo weak identification test critical values for all three models, suggesting that the instruments are weak, and the point estimates are very biased and seriously inconsistent, thus, it is unable to predict the magnitude of the effects accurately when applying IV models (Angrist, Imbens, & Rubin, 1996; Belzil, 2007; Murray, 2006; Stock & Yogo, 2002).

Separate regressions for each instrument (pre-treatment income, assets, and the distance to the nearest banks) were also run, and I observed that all of the test results accept the null hypothesis of weak instrument. In short, the potential instruments are weak, thus the conventional estimators provide less biased estimates than 2SLS/IV estimators do (Murray, 2006, Stock, 2010; Stock & Yogo, 2002).

In the above tests, with the joint estimation procedure (treatment participation and outcome equation), the normal distribution assumption of the first stage dependent variable was ignored even though it is a binary variable. This is because Wooldridge (2002) states that binary endogenous variable is not a problem, that is, one may ignore the assumption. The joint estimation procedure may be acceptable since non-fulfilment of the normality assumption may not be critical as it appears because the OLS still remain unbiased Gurajati (1995, p. 543). However, the estimates that ignored the assumption are woefully inefficient (Nichols, 2009).

Treatment effect model may be a solution to the problem of non-fulfilment of the normality assumption of binary endogenous variable in the first stage. The binary endogenous regressor (credit participation) is viewed as a treatment indicator, hence this estimation is considered as the treatment effect model. Error terms (u_i of main equation, and v_i of instrumental equation) are assumed to be correlated, that is, $cov(u_i, v_i) = \rho\sigma^2$ where $u_i \sim NID(0, \sigma^2)$ and $v_i \sim N(0,1)$. This model offers an estimator similar to IV estimator in the case of a single binary endogenous variable, and it improves efficiency of estimates (Nichols, 2009, p. 56). For the treatment effect model (*treatreg* in Stata®*)*, the Lambda or inverse Mills' ratio is estimated in the first stage and then is included in the second stage to correct for selection bias. Both manual 2SLS and *treatreg* provide consistent estimates, but the *treatreg* is more efficient because it uses information about the rest of the system that the 2SLS ignores. Accordingly, three models with the same specifications of the models in Appendix 5.7 Table 4 are regressed, and estimation results are presented in Appendix 5.7 Table 5. The purpose of the treatment effect model is to examine whether the first (treatment selection) and the second (outcome) model are independent. The Likelihood Ratio test results of independence between the selection equation and outcome equation (Ho: $\rho = 0$) accepts the Ho for all models at the 5% level. This casts doubt on the validity of instruments and weak instruments used in the models.

Appendix 5.7 Table 2: Hausman test for IVTOBIT model

Estimator	(1) Two-stage Tobit (β_i)	(2) Two-stage Tobit (β_i)	(3) Two-stage Tobit (β_i)	(4) Tobit (b_i)
Credit participation	902.00	-169.16	622.69	146.09
(standard error)	(408.67)*	(694.60)	(338.22)$^+$	(52.81)**
Controlling variables: Head's sex, age, education, marital status, number of school-age children, ward dummies	Yes	Yes	Yes	Yes
LR χ^2 (all coeffs=0)	61.63	58.37	60.19	58.16
Prob > χ^2	0.0000	0.0000	0.0000	0.0000
Pseudo R^2	0.0175	0.0166	0.0988	0.0165
First stage statistic				
Pseudo R^2	0.0927	0.0870	0.0988	
Wald χ^2 (all coeffs=0)	24.40	21.46	26.10	
Prob > χ^2	0.0066	0.0441	0.0251	
Excluded instruments	Pre-treatment income per capita in log, pre-treatment assets in log	Distance to the nearest bank within each ward	Pre-treatment income per capita in log, pre-treatment assets in log, distance to the nearest bank within each ward	No
Hausman test (H_0: b=β): χ^2	3.47	0.21	2.03	
Prob > χ^2	0.9426	1.0000	0.9909	

Comment: Hausman test results accept the hypothesis H_0 that difference in coefficients is not systematic, so conventional Tobit model is preferred.

Appendix 5.7 Table 3: Joint estimation of IVTOBIT model

	(1)	(2)	(3)
Credit participation coefficient (standard error)	978.55 (618.13)	-767.38 (1373.51)	611.82 (406.71)
Controlling variables: Head's sex, age, education, marital status, number of school-age children, ward dummies	Yes	Yes	Yes
Wald χ^2 (all coeffs=0)	31.16	26.29	46.77
Prob > χ^2	0.0003	0.0018	0.0000
First stage statistic			
Adjusted R^2	0.0670	0.0487	0.0586
F-statistic (all coeffs=0)	2.87	2.11	2.16
Prob > F	0.0021	0.0170	0.0100
Excluded instruments	Pre-treatment income per capita in log, pre-treatment assets in log	Distance to the nearest bank within each ward	Pre-treatment income per capita in log, pre-treatment assets in log, distance to the nearest bank within each ward
Wald test of exogeneity: χ^2	3.76	0.98	1.76
Prob > χ^2	0.0526	0.3220	0.1844

Comment: Wald test of exogeneity accepts the hypothesis H_0 that credit participation is exogenous, so IVTOBIT model is inappropriate.

Appendix 5.7 Table 4: Impact of credit participation on logarithm healthcare expenditure using IV estimator (LIML estimation)

Explanatory variables	(1)	(2)	(3)
Credit participation	7.9100	-4.6918	14.2241
	(4.7870)+	(5.9965)	(40.8714)
Head's gender (male=1)	0.3015	0.1288	0.3880
	(0.3771)	(0.3465)	(0.8931)
Head's age (year)	0.0626	-0.0304	0.1092
	(0.0378)+	(0.0462)	(0.3032)
Head's education	0.0208	0.0977	-0.0178
	(0.0639)	(0.0555)+	(0.2739)
Marital status (married=1)	0.4778	-0.8759	1.1560
	(0.7129)	(0.7432)	(4.4823)
Household size in log	-0.8341	1.9232	-2.2155
	(1.1406)	(1.3767)	(9.0070)
Constant	-4.0270	5.7811	-8.9413
	(3.8336)	(4.7795)	(31.8808)
Location controls (ward dummies)	Yes	Yes	Yes
F (9, 401)	1.97	2.12	0.54
Prob > χ^2	0.0415	0.0272	0.8456
Observations	411	411	411
First stage statistic			
Excluded instruments	Pre-treatment income in log, pre-treatment assets in log	Distance to nearest bank within each ward	Pre-treatment income, assets, distance to nearest bank
F-value (test for instruments jointly equal zero)	3.82	1.37	2.01
P-value in bracket	[0.0228]	[0.2425]	[0.0638]
Partial R^2	0.0146	0.0123	0.0275
IV tests (LIML IV estimation)			
Under-identification test (LM statistic): P-value in bracket	4.854 [0.0883]	4.905 [0.2971]	9.727 [0.1366]
Weak identification test (Wald F statistic)	3.816	1.373	2.006
Stock-Yogo weak ID test critical value at 10% maximal LIML size	8.68	5.44	4.45
Hansen J statistic (overid test): P-value in bracket	1.874 [0.1710]	1.555 [0.6695]	1.561 [0.9059]

*Robust standard errors in parentheses; +significant at 10%; * significant at 5%; ** significant at 1%*

Appendix 5.7 Table 5: Impact of credit participation on logarithm healthcare expenditure using Treatment Effect Model

Controls in wage equation	**(1)**	**(2)**	**(3)**
Head’s gender (male=1)	0.2159	0.1972	0.2130
	(0.1690)	(0.1730)	(0.1686)
Head’s age	0.0165	0.0065	0.0150
	(0.0069)*	(0.0056)	(0.0079)+
Head’s education	0.0589	0.0672	0.0602
	(0.0254)*	(0.0244)**	(0.0253)*
Marital status (married=1)	-0.1932	-0.3397	-0.2159
	(0.2174)	(0.2011)+	(0.2187)
Household size in log	0.5326	0.8309	0.5788
	(0.2375)*	(0.2111)**	(0.2717)*
Long Truong (LT)	0.8231	1.0142	0.8527
	(0.2481)**	(0.2314)**	(0.2535)**
Long Phuoc (LP)	0.7182	0.8943	0.7455
	(0.2637)**	(0.2483)**	(0.2674)**
Phuoc Binh (PB)	0.5160	0.5280	0.5179
	(0.2817)+	(0.2710)+	(0.2771)+
Credit participation	1.6638	0.3003	1.4528
	(0.6572)*	(0.4727)	(0.8877)
Constant	0.8345	1.8957	0.9987
	(0.6300)	(0.5495)**	(0.7717)
Wald chi2 (9): all coeffs=0	64.25	55.00	59.42
Prob > χ^2	0.0000	0.0000	0.0000
Observations	411	411	411
Wald χ^2 ($\rho = 0$)	2.82	0.67	0.97
Prob > χ^2 ($\rho = 0$)	0.0930	0.4142	0.3255
Controls in selection equation (first stage)			
Variables as of the wage equation	Yes	Yes	Yes
Pre-treatment income in log, pre-treatment assets in log	Yes	No	Yes
Distance to nearest bank within each ward	No	Yes	Yes

*Robust standard errors in parentheses; + significant at 10%; * significant at 5%; ** significant at 1%*

Chapter 6: Heterogeneous household credit impacts on the poor's spending: A quantile treatment effect and budget share analysis

6.1 Introduction

The impact of access to credit on the poor's consumption expenditure have been widely studied (Coleman, 1999; Rahman, Mallik, & Junankar, 2007; Nguyen, 2008; Pitt, Khandker, Chowdhury, & Millimet, 2003; Pitt & Khandker, 1998). However, the literature concentrates on finding average treatment effects (ATE), which assume that all 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, Gelbach, & Hoynes, 2006, 2008; Djebbari & 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 were 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 (e.g., 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 heterogeneity in treatment effects can be studied using a Quantile Treatment Effects (QTE) estimator.

In the current chapter, I report QTE estimates of the impact that access to credit has on the household spending of poor households in peri-urban areas of Ho Chi Minh City (HCMC), Vietnam. I used a survey designed by myself and applied to a sample of the poor who are under the urban poverty line.[64] Thus, 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. My results show that such an approach hides considerable within-group heterogeneity in the treatment effects.

[64] Set at VND 6 million per person per year, which is equivalent to about US$1 per day.

This chapter also uses the Seemingly Unrelated Regression Estimator (SURE) to analyze the impact of credit participation on budget shares and to provide baseline estimated impacts for comparing with those of QTE. Heterogeneity in the impacts is found in most cases; especially for healthcare budget share. While the ATE shows no effects of credit on the budget share for healthcare, the QTE finds significant effects for low healthcare spenders, even within this supposedly homogenous group of the poor.

The remainder of the chapter is organised as follows. The next section presents a theoretical background of household credit impacts on household budget shares. Section 6.3 describes estimation strategies. Section 6.4 reports empirical results, and the final section provides the finding summary.

6.2 Theoretical background

There have been several recent instances employing the QTE to examine the heterogeneity in treatment impacts (Ababie, Angrist, & Imbens, 2002; Bitler, Gelbach, & Hoynes, 2006, 2008; Firpo, 2007; Heckman, Smith, & Clemnets, 1997). Heckman et al (1997) were the first to examine the heterogeneity in the impacts, and they reject an important assumption of the conventional approach to program evaluation that all treated households get the same effect from the program participation. They find strong evidence of heterogeneity in the impact distributions using data from the National Job Training Program. Djebbari and Smith (2008), Galdo, Jaramillo, and Montalva (2008), and Dammert (2008) are the pioneers in investigating the heterogeneous program effects in developing countries. These studies show that program effects not only vary across subgroups (gender, age-groups, etc) but also change along the conditional distribution of outcomes, driven by unobserved characteristics.

Furthermore, exploring heterogeneous effects provides more information for policy intervention (Djebbari & Smith, 2008). One of their main findings is that program impacts are not uniformly distributed. Thus, the heterogeneous effect is not uniquely attributed to the observed characteristics. For example, the impact on wealth and nutrition is greater for households who were at a higher level of wealth and nutrition prior to program participation. They suggest that the variance of the impact is very important, and the higher the variance of impacts the less relevant the ATE is. Consequently, policy intervention might be more effective when one knows program effects at different points of the outcome distribution. In other words, policy-makers should have knowledge about those who are at different points of the outcome distribution, and what the effect is at those points, in order to properly target the policies. Similarly, Dammert (2008) finds heterogeneity in impacts of cash transfer program on the distribution of food expenditure. Hence, the impacts on *per capita* food expenditure increase from the lowest percentile to the highest percentile of the distribution. In contrast, for the *share* of food expenditure, the effect decreases from the lower percentiles to the higher percentiles; in other words, the impact is lower for households that have higher levels of food shares prior to credit participation. Therefore, Dammert concludes that there is considerable heterogeneity in the impacts of the program on the distribution of expenditure, which is ignored in ATE models. Thus, the success of a program intervention depends on more than the mean effects. Similarly, Bitler, Gelbach, and Hoynes (2006) find heterogeneity in the impact of the US welfare reform across the outcome distribution, with zero-effect on earnings for the bottom half of the distribution, but higher effect for the upper part of distribution except the very top percentiles. Heterogeneous impacts on income and transfers are also found by the study at different points on the outcome distribution.

In summary, studies using quantile treatment effect estimation so far have come up with a consistent conclusion that the impacts vary across the outcome distribution. Thus, the QTE provides a more detailed picture of the program effects than that is obtained by ATE models.

6.3 Analytical framework[65]

6.3.1 Seemingly unrelated regression estimator (SURE)

When considering simultaneously the impacts of household credit on all sorts of consumption expenditure, one should analyze a system of equations. Moreover, to set a baseline for comparison with QTE estimates,[66] one may need to run the SURE model using the same set of covariates. So far, there have been few investigations into credit impacts on household consumption using a system of equations. Empirically, consumption expenditure analysis has attracted more attention; the main purpose of these analyses is to estimate the Engel curve and

[65] Sample design and data collection were discussed in Chapter 1.

[66] Instead of setting OLS estimate baselines for the comparison, SURE provides the same estimates of coefficients (only standard errors are different). Moreover, SURE is a more efficient estimator than its OLS counterpart. I will discuss this issue in the next section.

income elasticity of demand for items of interest (e.g. food). Deaton (1997) provides a useful framework for this direction of the research. Some research on the topic can be found in Holcomb, Park and Capps (1995) and Chern et al (2003). In these studies, the Working-Leser model is employed (Working, 1943; Leser, 1963, 1976). To the best of my knowledge, Rahman et al (2007) are the first effort to examine the impact of household credit on consumption behaviour using the SURE model. They find that borrowers are better off in terms of both food and non-food items.

The system of budget share equations are potentially linked by the covariance structure of their disturbances and also tied together by the adding-up restriction; hence the residuals of the equation system are simultaneously correlated. In this case, the SURE is an appropriate estimator (Zellner, 1962). Typically, the estimation of cross-section budget shares for several commodities is done with the SURE estimator. Canonical examples are estimation of the income elasticity of demand for a particular set of goods (Deaton, 1997; Holcomb et al, 1995; Chern et al, 2003; Rahman et al, 2007).[67]

Typically these income elasticities are estimated from Engel curves for budget shares, and while there are several functional forms available.[68] The Working-Leser (Working, 1943; Leser, 1963) is often used. The Working-Leser equation is as follows:

$$w_i = \alpha + \beta_1.\ln(y_i) + \beta_2.\ln(hhsize)_i + \varepsilon_i \quad (6.1)$$

where w_i is the budget share of a particular commodity i to total expenditure, ln(y) is the natural logarithm of monthly average expenditure per capita (per capita expenditure is used to take into account consumption behaviour across households),[69] ln(hhsize) is the natural logarithm of household size.

This functional form allows the whole sample to be used even though some households may not purchase certain goods, and so have zero budget shares

[67] I might apply An Ideal Demand System (AIDS) model (Deaton & Muellbauer, 1980), but relative price is not available, hence budget share of each item is independent of the price of the other if real expenditure (x/P) is held constant. Moreover, I collected cross-sectional data from 4 wards in a small peri-urban area of HCM City, thus prices are assumed to be constant across households in the area, so the AIDS model becomes the Engel curve.
[68] See Holcomb et al (1995) for more detailed discussion.
[69] Regressions on either natural logarithm of monthly average expenditure per capita or natural logarithm of monthly average expenditure result in the same results of all coefficients except that of ln(hhsize).

(Deaton, 1997, p. 304). The model is claimed to fit better than other alternatives (Leser, 1963, 1976).

The effect of household credit on the budget share will be examined by including in equation 6.1 a credit participation variable (D) and also controlling for location difference effects. The regression model now is as follows:

$$w_i = \alpha + \beta_1.\ln(y_i) + \beta_2.D_i + \beta_3.\ln(hhsize)_i + \beta_4.warddummy_i + \varepsilon_i \qquad (6.2)$$

One potential problem here is the endogeneity of some explanatory variables, including credit participation status. One may use instruments to first predict credit participation, and then use this predicted value in place of the original variable of credit participation. However, I am unable to apply this IV model since there are no good instruments available (see discussion in Appendix 5.7, Chapter 5). Thus, I apply only the standard SURE to estimate a system of three equations for education, healthcare, and food.[70]

6.3.2 Heterogeneity in treatment effects: Quantile treatment effects (QTE)

The Quantile Regression (QR) estimator examines the effects of the regressors on the dependent variable at various points on the conditional distribution of responses (e.g. at the 25th, and 75th percentiles). Quantile regression (QR) was first introduced by Koenker and Bassett (1978); see also Koenker and Hallock (2001). The model specifies the θ^{th} – quantile ($0< \theta <1$) of the conditional distribution of the dependent variable, given a set of covariates x_i, and assumes that residual distributions of each quantile are normally distributed as follows:

$$Q_\theta(y_i \mid x_i) = \alpha_\theta + x_i.\beta_\theta \qquad (6.3)$$

where y_i is the outcome of interest (the budget share for each household expenditure group in my 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 gender, age, marital status, and education, along with household size, household expenditure, initial income, initial assets, and location of the dwelling. The treatment variable of interest is credit participation, which equals one if a household had any loans in the 24 months prior to the survey and zero

[70] Results for the other expenditure are from the adding-up restriction (i.e. $\Sigma w_i = 1$, thus $\Sigma\alpha_i = 1$ and $\Sigma\beta_i = 0$).

otherwise. A total of 304 households were borrowers, and 107 households were non-borrowers under this definition. The estimator (equation (6.3)) is the solution to the following minimization problem (Cameron & Trivedi, 2009):

$$Q(\beta_\theta) = \min_\beta \sum_{i=1}^{n} \left[\left| y_i - X_i\beta_\theta \right|\right] = \min\left[\sum_{i:\, y_i \geq x_i\beta} \theta \,|\, y_i - x_i\beta_\theta \,| + \sum_{i:\, y_i < x_i\beta} (1-\theta) \,|\, y_i - x_i\beta_\theta \,| \right] \quad (6.4)$$

In other words, the equation is the solution to a problem where the sum of the weighted absolute value of the residuals is minimised. As θ is increased, the entire distribution of outcome y is traced, conditional on X_i. We estimate β_θ for each particular quantile rather than just β. If we estimate β_θ for θ, then much more weight is placed on prediction for observations with $y \geq x_{i.}\beta$ than for observations at 1-θ with $y < x_{i.}\beta$.

In one of my dependent variable, the education budget share, the data are left-censored at zero. The outcome y_i in equation (6.3) and (6.4) is replaced by y_i^*. We do not observe y^* but rather y (Johnston & Dinardo, 1997, p. 442-445), where

$$y_i = \begin{cases} y_i^* & \text{if } y_i^* > 0 \\ 0 & \text{if } y_i^* \leq 0 \end{cases}$$

The estimation procedure for the censored quantile regression (*qcenreg*) is based on Wilhelm (2008) and Chernozhukov and Hong (2002).

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 (Δ_θ) 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, & 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, the QTE is simply the difference between the same quantile of the marginal distributions of outcomes for the treated households and for comparison group households.

The reason for using the QTE estimator is that the effect is different across points on the outcome distribution, while the OLS estimator estimates the conditional mean of the outcome distribution. The QTE provides a "much more complete picture" (Koenker & Hallock, 2001, p. 144). For example, Chamberlain (1994) finds that the effect of union on wage premium declines monotonically from 28% at the first deciles to 0.3% at the upper deciles. Moreover, the QR is able to show any tendency for a dispersion of budget shares as total household income or expenditure increases (Deaton, 1997; Koenke & Hallock, 2001).

Heterogeneity in the outcome variable may correspond to either variation across particular sub-groups (or cohorts) in the population that would generate a local average treatment effect (LATE) or impacts of unobservable characteristics (Angrist, 2004). In the current chapter, I assume that the sample population is homogeneous since they are all under the poverty line, hence there are no sub-groups that would have the LATE (and for whom a particular instrumental variable might bind, while it does not bind for others), and the heterogeneity in the outcomes is assumed to come from the random errors. Since I assume it is unobservables rather than local treatment effects causing the heterogeneity, I 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 & Imbens, 2002)). If good instruments were available, the QTE with instrumental variables (IQTE) may be more precise than the conventional IV estimator at the median (Abadie, Angrist, & 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 (Appendix 5.7 in Chapter 5), hence I rely on the assumption that selection into the treatment is based on observables.

6.4 Empirical results

In this section, the SURE is first applied in Section 6.4.1 to estimate average treatment effects of credit participation on budget shares and on the income elasticity of demand for different household expenditure groups. This analysis will set a comparative baseline to investigate the heterogeneity in the impact of credit participation in the following section. Section 6.4.2 presents the heterogeneous impacts of household credit by applying the Quantile Treatment Effect estimator.

6.4.1 Impacts of credit participation on household budget shares

Estimates of the impacts of credit on household budget shares are in the left panel of Table 6.1. Household expenditure is divided into 4 groups: education, healthcare, food, and the remaining expenditure (called *others*). The unconditional means of budget shares for these four groups are 5.35%, 6.15%, 52%, and 36.5% respectively. Due to the adding-up restriction, budget share of any one expenditure group is excluded from the regressions. These models control for household size in logarithm, expenditure per capita in logarithm, and location dummies (basic specification). Results from extended specification that are controlled for variables in the basic specification and are further controlled for household head’s gender, education, age, marital status, pre-treatment income per capita and assets, are reported in the right panel of Table 6.1. The Breusch-Pagan test of independence of each equation in the system of equations rejected the hypothesis of independence at the 1% level for all models.

According to results in Table 6.1, credit participation resulted in a significant increase in the budget share of education, and a decline in the budget share of food. The budget shares of healthcare and the other expenditure are positively affected by credit participation, but the effects are not statistically significant. The signs and magnitudes of impacts on the budget shares are similar when controlling further for household head’s gender, education, age, marital status, pre-treatment income per capita, and pre-treatment assets (the extended models on the right panel of Table 6.1).[71] These findings are also consistent with the finding in the preceding chapter. It is likely that households who borrowed gave more priority to child education and healthcare spending, even though they were poor.

Apart from the focus on credit participation, the Working-Leser equation is also used to estimate the income elasticity of demand, which is calculated as follows (White & Masset, 2002, p. 12):

$$\text{Income elasticity}_{\mathrm{i}} = 1 + \beta_i.(\mathrm{X/Y_i}) = 1 + \beta_i.\frac{1}{\mathrm{Y_i/X}} = 1 + \beta_i \frac{1}{budgetshare_i}$$

where Y_i is monthly expenditure for group of good i, β_i is the estimated coefficient from Working-Leser equation, X is monthly average household expenditure per capita in natural logarithm. The $budgetshare_i$ (Y_i/X) is the budget share of the corresponding expenditure for group of good i. For example, using values from Table 6.1 (the right panel), the income elasticity of demand for education is calculated as 1+ 0.0043*1/5.35%=1.08. The income elasticity of demand for food, health, and the other expenditure is 0.83, 1.41, and 1.16, respectively.[72] Accordingly, the estimates indicate that education, healthcare, and the other expenditure are luxury goods, whereas food is a necessity good for the poor.

The finding here is opposite to a common belief (e.g. Rahman et al, 2007), that the poor often spend more on food when they have money from microcredit. My estimation results show that when poor households borrow, they commit larger budget shares to long-term investment in human capital formation such as education and healthcare spending. This consumption pattern of the poor is very significant for poverty reduction policies.

Furthermore, one may think that borrowers and non-borrowers have different income elasticities of demand, i.e. they have different coefficient slopes of monthly average expenditure per capita (in logarithm). To check this, I added an interaction term between the credit participation status and the expenditure per

[71] Correlation coefficients between the expenditure per capita and the pre-treatment variables are quite low (<0.22), moreover, controlling for these initial wealth indicators will reduce the bias in the impact estimates (Mosley, 1997).

[72] This is income elasticity of demand for food, it is slightly higher than that of Vietnam, 0.8 in 1992, 0.75 in 1998 (White & Masset, 2002) but is perceivable because the households in my survey are poor so the demand for food is more elastic than that of general households.

capita. I ran both the basic and extended model and observed that all the coefficients of the interaction terms of all equations for education, health, food, and the other (remaining) expenditure are very small and not statistically significant at the conventional levels (the estimates are not reported). Consequently, borrowers and non-borrowers have the same income elasticity of demand because both groups are poor and hence their consumption behaviours are likely to be identical.

Overall, credit participation positively influences budget shares of non-necessity goods such as education, health, and other non-food items, but negatively affects necessity goods (food). In other words, households who borrowed have lower food shares. Since food share is an (inverse) proxy measure of welfare (Engel's law), this suggests that borrowing households are better off even after controlling for initial characteristics.

6.4.2 Quantile treatment effect estimation

In this section, I first examine unconditional monthly average consumption of education, healthcare, food and 'other' expenditure and their budget shares for borrowers and non-borrowers at the 25^{th}, 50^{th}, 75^{th} percentile and the mean values (Table 6.2). Borrowers spent more than non-borrowers at any percentiles, and for all groups of expenditures. For education, healthcare, and the other expenditure, borrowers had higher budget shares than non-borrowers at all quartiles examined. Thus, borrowing households are spending more in absolute terms and also devoting a larger share of their budgets to capital human formation (education and healthcare) and other non-food expenditure at all points in the distribution. In contrast, the observed budget share of food spending is lower for borrowers than non-borrowers even though borrowers' absolute spending on food is higher.

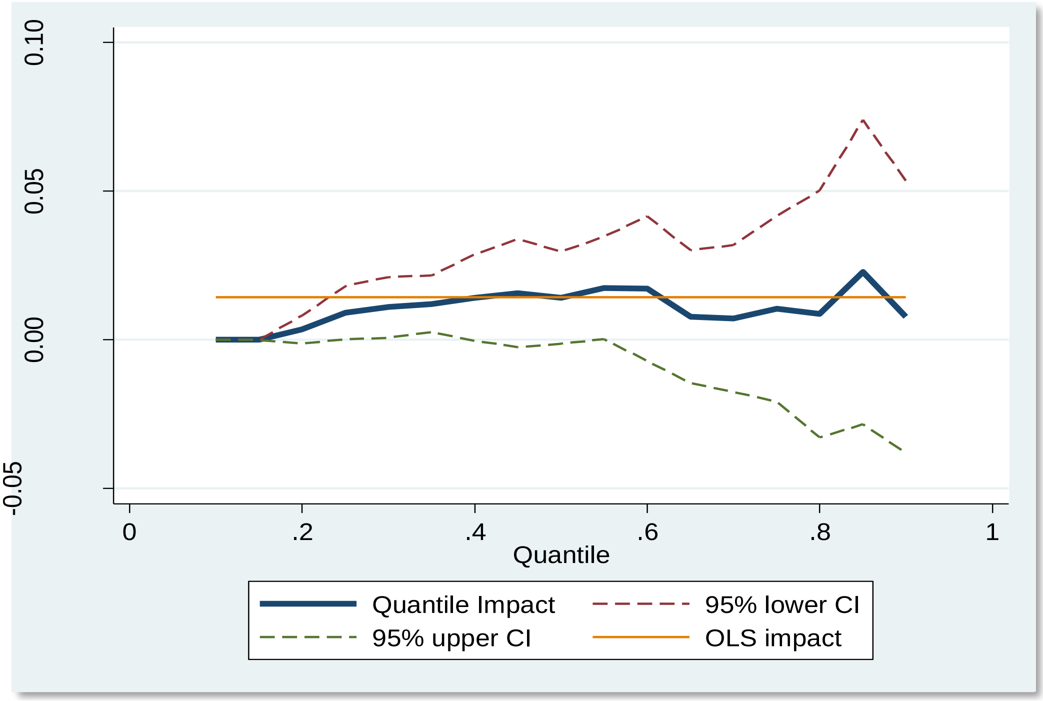
To test whether the higher human capital spending of borrowers across the distribution persists when conditioning on explanatory variables, I estimate quantile treatment effects at the 25^{th}, 50^{th}, and 75^{th} percentiles (Tables 6.3 to 6.6). The tables also present SURE estimates in the last column of each panel.[73] The explanatory variables used are listed in Appendix 6.1. My basic specification includes location, household size, and expenditure per capita in addition to the

[73] SURE and OLS estimates are the same except for their standard errors, thus to compare QTE estimates to OLS estimates one can use SURE estimates instead of OLS impact estimates; furthermore we are not able to efficiently estimate OLS impact for education budget share due to left-censored data.

credit participation treatment variable, while an extended specification adds the gender, age, marital status, and education of the household head, and pre-treatment income per capita, and pre-treatment assets.[74]

Credit participation has positive impacts on the budget share for education (Table 6.3). The impact is heterogeneous across the distribution of the outcome, and higher significant effects are found at the median and upper percentiles of the distribution (75th percentile) of budget shares. This apparent heterogeneity disappears after controlling for head's gender, age, education, pre-treatment income, and pre-treatment assets (the extended model in the right-panel of Table 6.3). A graphical depiction of this pattern is shown in Figure 6.1. Accordingly, the impact is detected higher from the 25th to 60th percentiles, and lower from 65th to 80th percentiles except for the very top (extreme observations) and below the 25th percentile.[75]

Figure 6.1: Credit impact on education budget share



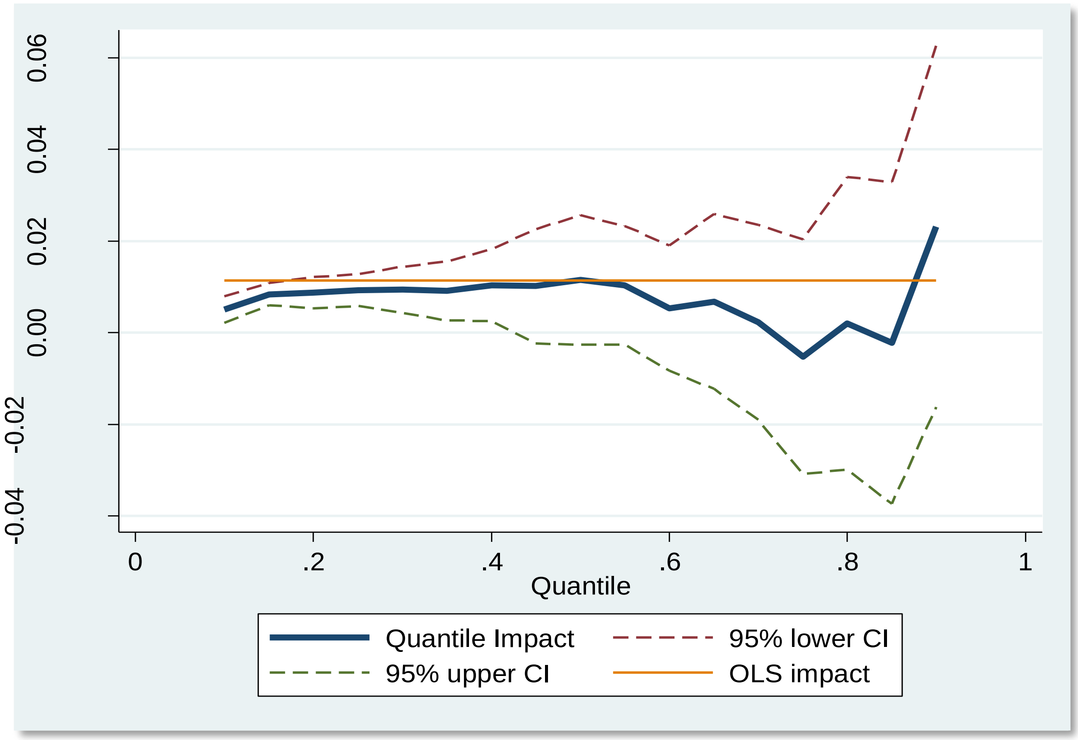
In both the basic and extended specification, there is considerable heterogeneity in the treatment effects of credit on the healthcare budget share (Table 6.4). For households with health budget shares below the median, access to credit is associated with significantly higher healthcare spending. But for

[74] Descriptive statistics for these variables and the tests of their differences between borrowers and non-borrowers are presented in Appendix 6.1.

[75] Unless stated, the Figures use parts of outcome distribution within the range (0.1 – 0.9) to avoid influences of few extreme observations on the graphs (Chernozhukov, 2000), and Figures are built on the extended model estimates.

households above the median, healthcare spending goes down (insignificantly) when a household is a borrower, except for the very top percentiles (above 85th, but the effect at the very top percentiles is insignificant) (Figure 6.2). The same pattern is observed when using the extended model specification. In neither case would these effects be apparent when using OLS or SURE.

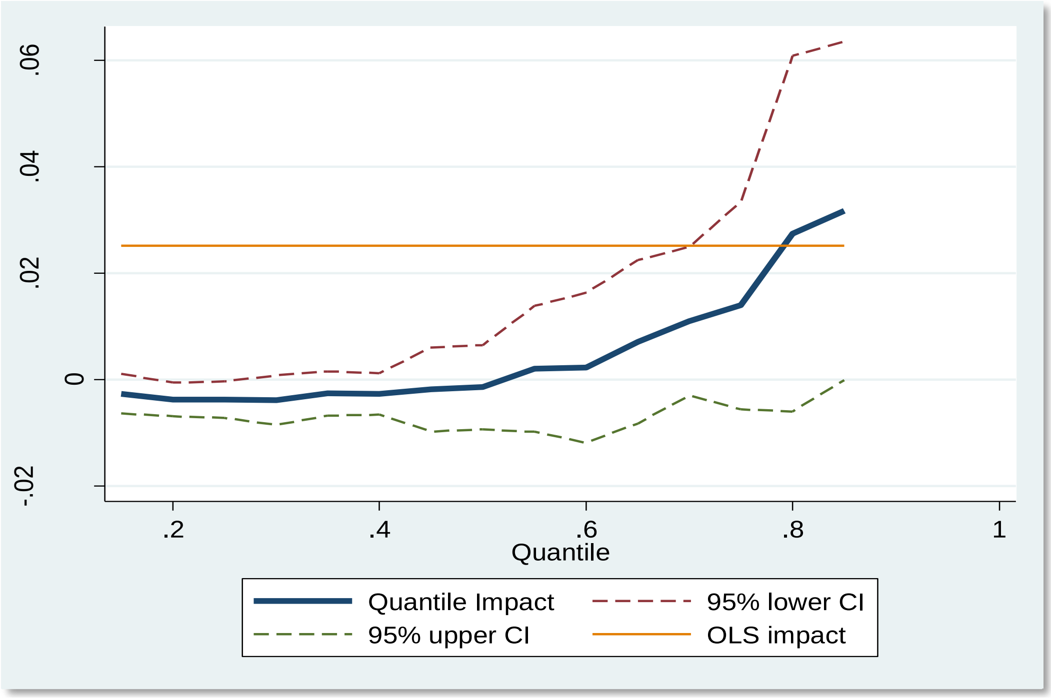
Figure 6.2: Credit impact on healthcare budget share



Hence it seems that access to credit increases the healthcare budget share of households that 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 is for a homogenous group of peri-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 (Figure 6.3). The SURE 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.

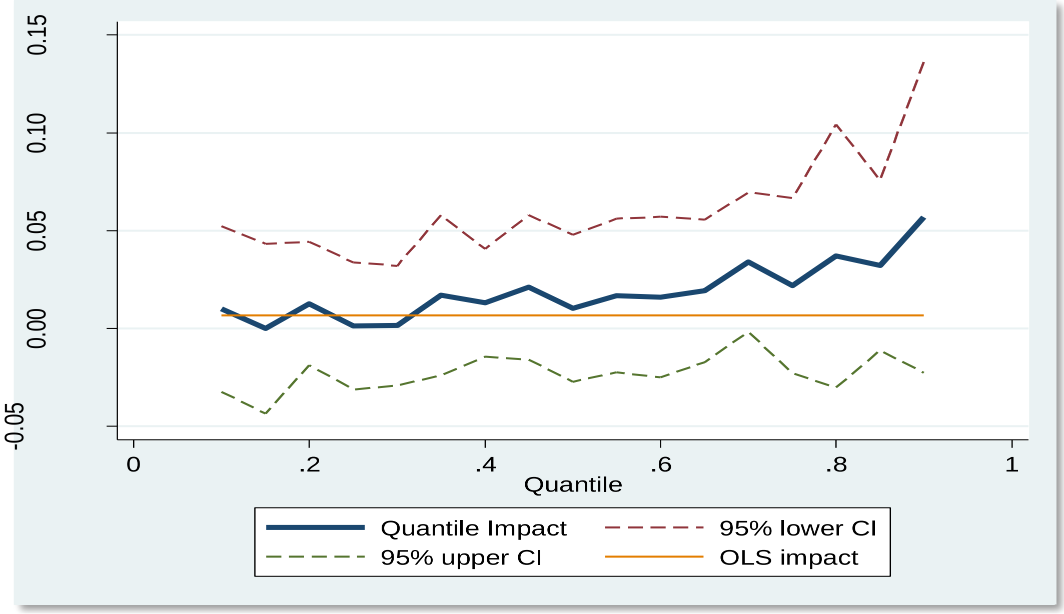
Figure 6.3: Impact of expenditure per capita on healthcare budget share



Contrary to the credit impacts on education and healthcare budget shares, the effect of household credit on the budget share of food is negative and statistically significant at the lower, median and upper percentiles (Table 6.5). Controlling further for head's gender, age, education, pre-treatment income and assets, the effect above the median are smaller but still significant at the 10% level. The effect on the budget share for food is stronger (negative) at the lower percentile (about -6%), about -4% at the median, and lower (about -3%) at the upper percentiles. This finding is consistent with Dammert (2008) and indicates lower impacts of credit for households that had higher food shares prior to credit participation.

Finally, I observe positive (but insignificant) effects of household credit on the shares of the remaining expenditure (housing, daily and annually non-food consumption expenditure), and the effect is stronger at higher percentiles on the distribution (Table 6.6 and Figure 6.4). The finding is consistent across models when controlling for a full set of covariates.

Figure 6.4: Credit impact on the other budget share



6.5 Finding summary and conclusions

The estimates by both SURE and QTE uncover that household credit impacts negatively and significantly on the budget share of food, whereas it affects positively on non-necessity goods, especially on education and healthcare expenditure groups. Contrary to a common belief that the poor often think of eating and other daily spending on necessity goods when they have money on hand, especially a marginal dollar, this study shows that the poor obviously give more priority to human capital spending than current eating, especially households whose budget shares for education and healthcare are relatively low prior to credit participation. Education and healthcare budget shares increased when the poor borrowed. Therefore, easing access to credit sources is likely to help steadily alleviate poverty in future due to the poor's improved human capital.

Treatment effects can vary widely, not only across sub-groups but also along the distribution of outcomes. This chapter provides evidence where my sample is all under the poverty line of about US$1 per day and would typically be considered one identifiable sub-group, for whom an average treatment effect would be estimated. Yet I find some heterogeneity in treatment effects within this seemingly homogenous sample, which would be hidden if only an average treatment effect is reported. Specifically, the QTE estimator provides clearer evidence of the effects than the OLS/SURE counterparts especially for the healthcare budget share. While OLS/SURE estimates of the ATE show no significant effect of credit participation on healthcare budget shares, the QTE estimates show that credit has positive impacts on healthcare budget shares for households with low levels of healthcare spending prior to borrowing. From a policy point of view, this suggests that facilitating access to credit sources could be a significant factor in improving the health of the urban poor.

TABLES

Table 6.1: Working-Leser Equation by Seemingly Unrelated Regression (SURE)

	Basic model				Extended model specification			
	Education	Health	Food	Others	Education	Health	Food	Others
Credit	0.0180	0.0088	-0.0352	0.0084	0.0115	0.0114	-0.0296	0.0067
	(0.0069)**	(0.0105)	(0.0158)*	(0.0152)	(0.0070)+	(0.0107)	(0.0162)+	(0.0157)
Lsize	0.0243	-0.0120	-0.0568	0.0445	0.0313	-0.0108	-0.0693	0.0488
	(0.0067)**	(0.0102)	(0.0153)**	(0.0147)**	(0.0072)**	(0.0111)	(0.0168)**	(0.0162)**
Lpcx	0.0040	0.0303	-0.0925	0.0582	0.0043	0.0252	-0.0894	0.0599
	(0.0061)	(0.0092)**	(0.0139)**	(0.0133)**	(0.0065)	(0.0099)*	(0.0149)**	(0.0145)**
Ward LT	-0.0049	0.0269	0.0401	-0.0621	0.0004	0.0346	0.0303	-0.0654
	(0.0084)	(0.0129)*	(0.0193)*	(0.0186)**	(0.0090)	(0.0138)*	(0.0208)	(0.0201)**
Ward LP	-0.0172	0.0184	0.0566	-0.0578	-0.0131	0.0254	0.0482	-0.0605
	(0.0084)*	(0.0128)	(0.0191)**	(0.0184)**	(0.0084)	(0.0129)*	(0.0194)*	(0.0188)**
Ward PB	0.0047	0.0272	0.0460	-0.0778	0.0082	0.0224	0.0536	-0.0842
	(0.0095)	(0.0145)+	(0.0217)*	(0.0209)**	(0.0097)	(0.0150)	(0.0225)*	(0.0218)**
Constant	-0.0173	-0.1475	1.2111	-0.0463	0.0874	-0.3459	1.3190	-0.0606
	(0.0446)	(0.0681)*	(0.1020)**	(0.0983)	(0.1021)	(0.1570)*	(0.2363)**	(0.2289)
Wald χ^2	34.90	20.16	70.35	40.33	57.90	35.32	82.59	46.61
Prob > χ^2 (all coeff=0)	0.0000	0.0026	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000
Observations	411	411	411	411	411	411	411	411

*Notes: Standard errors in parentheses; + significant at 10%; * significant at 5%; ** significant at 1%. Dependent variables are budget shares. Lsize is household size (in log); Lpcx is monthly expenditure per capita (in log). The extended model specification in the right panel controlled further for head's gender, age, marital status, education, and pre-treatment income per capita and asset. Breusch-Pagan test of independence for a system of (education, health, and food equation -basic model): $\chi^2(3)$ =72.709; (education, health, and the other expenditure equation−basic model): $\chi^2(3)$ =50.247; (education, health, and food equation -extended model): $\chi^2(3)$ = 70.012; (education, health, and the others equation−extended model): $\chi^2(3)$ = 50.893. The other expenditure (Others) includes housing, daily and annually non-food expenditure.*

Table 6.2: Monthly average consumption of borrowers (B) and non-borrowers (NB)

Expenditure Category	Mean		25th percentile		50th percentile		75th percentile	
	B	NB	B	NB	B	NB	B	NB
Education[a] expenditure	345.91 (7.48)	247.23 (6.35)	87.92 (2.68)	51.5 (2.05)	237.5 (5.89)	155.83 (4.14)	475.42 (10.01)	368.33 (10.06)
Education[b] expenditure	269.10 (5.90)	155.25 (3.78)	000 (0.00)	000 (0.00)	160.08 (4.09)	40.42 (1.93)	399.17 (9.04)	214.58 (5.31)
Health expenditure	299.67 (6.43)	220.84 (5.31)	63.17 (1.84)	12.08 (0.61)	119.67 (3.37)	69.67 (2.26)	290.42 (7.50)	185.00 (6.06)
Food expenditure	2122.60 (50.80)	1874.30 (55.64)	1373.79 (42.82)	1005.94 (46.28)	1855.63 (51.87)	1560.00 (56.69)	2581.19 (60.08)	2392.00 (65.56)
Other expenditure	1724.72 (36.88)	1351.80 (35.27)	848.08 (28.04)	609.03 (25.55)	1287.58 (35.32)	1011.17 (33.51)	1896.29 (43.27)	1583.33 (40.68)
Total expenditure	4416.10 (100)	3602.19 (100)	2791.29 (100)	1974.51 (100)	3719.43 (100)	2917.79 (100)	5084.94 (100)	4811.60 (100)

Notes: [a] average consumption on education expenditure is calculated for a sub-sample of households having children from 6 to 18 years old; [b] is for the whole sample. The budget shares are in the parentheses. B stands for Borrowers and NB stands for Non-borrowers.

Table 6.3: Censored quantile regressions of credit impact on budget share of education

Explanatory Variables	Basic specification				Extended model specification			
	0.25	0.50	0.75	SURE[a]	0.25	0.50	0.75	SURE
Credit	0.0260	0.0183	0.0275	0.0180	0.0143	0.0142	0.0112	0.0115
	(0.016)	(0.010)+	(0.014)*	(0.007)**	(0.030)	(0.012)	(0.015)	(0.007)+
Lsize	0.0241	0.0351	0.0431	0.0243	0.0268	0.0396	0.0572	0.0313
	(0.012)*	(0.009)**	(0.019)*	(0.007)**	(0.024)	(0.012)**	(0.018)**	(0.007)**
Lpcx	0.0024	0.0038	0.0050	0.0040	0.0022	-0.0009	0.0121	0.0043
	(0.008)	(0.007)	(0.016)	(0.0061)	(0.015)	(0.010)	(0.015)	(0.0065)
Constant	-0.0610	-0.0473	-0.0335	-0.0173	0.0283	0.0428	-0.0017	0.0874
	(0.071)	(0.049)	(0.118)	(0.0446)	(0.330)	(0.137)	(0.199)	(0.1021)
Obs[b]	269	382	407	411	230	373	403	411

*Notes: Bootstrap standard errors in parentheses with 1,000 replications; + significant at 10%; * at 5%; ** at 1%. SURE standard errors are not bootstrapped. Dependent variable is budget share of education. Lsize is household size (in log); Lpcx is monthly expenditure per capita (in log). Both the basic and extended models controlled for location dummies, while the extended model specification controlled further for head's sex, age, marital status, education, pre-treatment income per capita, and pre-treatment assets. [a]OLS and SURE magnitudes of coefficients are identical, but SURE is more efficient than OLS, thus, is employed here. [b]Due to the fact that the probabilities of being censored at different percentiles are different, controlling for observed characteristics, hence numbers of observations for each model at each percentile are not the same.*

Table 6.4: Quantile regressions of credit impact on budget share of healthcare expenditure

Explanatory variables	Basic specification				Extended model specification			
	0.25	0.50	0.75	SURE	0.25	0.50	0.75	SURE
Credit	0.0078	0.0060	-0.0009	0.0088	0.0093	0.0115	-0.0053	0.0114
	(0.002)**	(0.006)	(0.016)	(0.0105)	(0.002)**	(0.006)+	(0.016)	(0.0107)
Lsize	0.0029	0.0048	0.0139	-0.0120	0.0020	0.0034	0.0061	-0.0108
	(0.0020)	(0.006)	(0.013)	(0.0102)	(0.003)	(0.007)	(0.014)	(0.0111)
Lpcx	-0.0021	0.0004	0.0287	0.0303	-0.0037	-0.0014	0.0140	0.0252
	(0.0015)	(0.004)	(0.01)**	(0.009)**	(0.002)*	(0.005)	(0.012)	(0.0099)*
Constant	0.0110	0.0037	-0.1547	-0.1475	-0.0102	-0.0764	-0.3048	-0.3459
	(0.0114)	(0.032)	(0.063)*	(0.068)*	(0.027)	(0.052)	(0.133)*	(0.1570)*

Notes: Dependent variable is budget share of healthcare; number of observations is 411 households; otherwise see Notes in Table 6.3.

Table 6.5: Quantile regressions of credit impact on budget share of food expenditure

Explanatory Variables	Basic specification 0.25	0.50	0.75	SURE	Extended model specification 0.25	0.50	0.75	SURE
Credit	-0.0462	-0.0448	-0.0479	-0.0352	-0.0581	-0.0384	-0.0302	-0.0296
	(0.021)*	(0.021)*	(0.017)**	(0.0158)*	(0.024)*	(0.021)+	(0.018)+	(0.0162)+
Lsize	-0.0517	-0.0541	-0.0563	-0.0568	-0.0684	-0.0545	-0.0611	-0.0693
	(0.025)*	(0.025)*	(0.018)**	(0.0153)**	(0.031)*	(0.026)*	(0.024)*	(0.0168)**
Lpcx	-0.1044	-0.0947	-0.0772	-0.0925	-0.1023	-0.0775	-0.0640	-0.0894
	(0.025)**	(0.028)**	(0.019)**	(0.0139)**	(0.027)**	(0.028)**	(0.023)**	(0.0149)**
Constant	1.1755	1.2593	1.2359	1.2111	1.1416	1.4443	1.5268	1.3190
	(0.168)**	(0.203)**	(0.134)**	(0.1020)**	(0.466)*	(0.427)**	(0.340)**	(0.2363)**

Notes: Dependent variable is budget share of food; number of observations is 411 households; otherwise see Notes in Table 6.3.

Table 6.6: Quantile regressions of credit impact on budget share of the other expenditure

Explanatory Variables	Basic specification 0.25	0.50	0.75	SURE	Extended model specification 0.25	0.50	0.75	SURE
Credit	0.0144	0.0041	0.0338	0.0084	0.0014	0.0104	0.0219	0.0067
	(0.016)	(0.0175)	(0.023)	(0.0152)	(0.018)	(0.018)	(0.023)	(0.0157)
Lsize	0.0441	0.0546	0.0339	0.0445	0.0454	0.0497	0.0541	0.0488
	(0.016)**	(0.021)*	(0.025)	(0.0147)**	(0.017)**	(0.023)*	(0.030)+	(0.0162)**
Lpcx	0.0366	0.0484	0.0702	0.0582	0.0271	0.0450	0.0848	0.0599
	(0.021)+	(0.025)+	(0.026)**	(0.0133)**	(0.021)	(0.025)+	(0.027)**	(0.0145)**
Constant	-0.0423	-0.0081	-0.0316	-0.0463	-0.3529	-0.3873	0.1675	-0.0606
	(0.155)	(0.170)	(0.182)	(0.0983)	(0.313)	(0.363)	(0.406)	(0.2289)

Notes: Dependent variables are budget share of the remaining expenditure (others); number of observations is 411 households; otherwise see Notes in Table 6.3.

APPENDICES

Appendix 6.1: 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	299.67	582	220.84	552	1.25
Health budget share	0.0643	0.092	0.0531	0.0929	1.07
Household size in log	1.554	0.440	1.354	0.577	3.26**
Total monthly expenditure	4,416.1	2738	3,602.2	2,597	2.75**
Monthly expenditure per capita in log	6.691	0.484	6.611	0.596	1.25
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	3.35	4.664	3.76	0.60
Married (yes=1)	0.648	0.478	0.607	0.491	0.74
Head's age (year)	52.901	13.97	59.467	15.46	3.87**
Initial assets incl land & 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.

Chapter 7: Household credit to the poor and its impacts on child schooling

7.1 Introduction

It is widely recognised that human capital plays an important role in productivity, earnings, and sustainable poverty reduction (Maldonado & Gonzalez-Vega, 2008; Maitra, 2003). Education not only passes specific knowledge to students but also enhances skills in acquiring new knowledge (Rosenzweig, 2010). However, the poor encounter two key development issues: income constraints and low education. These lead to a vicious circle of poverty. Income constraints result in low education investment and hence low education attainment. Low education results in low productivity and then low income. Hence, child schooling receives a lot of attention in development strategies and is considered a solution to breaking the vicious circle of poverty and to enhancing future development. However, education investment by many households in developing countries is insufficient, especially by poor households.

Demand for education relies on parents' motivation, income constraints, and competing demands for children's time (Maldonado & Gonzalez-Vega, 2008). Under perfect financial markets, credit would be a tool to guarantee full investment in education. The underdevelopment of financial markets and income constraints, however, are the main reasons for deficient education for children in developing countries (Edmonds, 2006; Jacoby & Skoufias, 1997; Ranjan, 2001). Due to credit constraints, many households are not able to borrow or borrow insufficiently so they may pull their children out of school or ask their children to reduce study time and go to work, especially when households face adverse shocks (Kurosaki, 2002). Thus, access to credit would help households to smooth consumption without the need to cut children's schooling.

Moreover, during the economic transition in Vietnam cuts to public subsidies in education have led to an increase in private education costs (Cloutier, Cockburn & Decaluwe, 2008). As a result, households, especially the poor, may need other external support, including credit, for their children's education. This chapter aims to evaluate the impacts of household credit on child schooling for the poor in peri-urban areas of Ho Chi Minh City (HCMC), Vietnam. The chapter has two goals: *First*, it examines whether borrowing keeps children in school longer than without borrowing. *Second*, the chapter examines whether the sources of credit and gender of children matter in impacts on child schooling. This chapter finds that although small loans may affect levels of education spending, but they just bring slight benefits to the poor's child schooling. This is because the loan amounts are too small, especially amounts of informal credit, to cover "big" lump sums of education expenses for initial enrolments, and hence small loans do not affect parents' longer-term decisions about their children's schooling.

This chapter is organised as follows: The next section reviews the literature on credit impacts on child schooling. Section 7.3 discusses estimation methods. Section 7.4 reports estimation results and Section 7.5 provides concluding remarks.

7.2 Literature on credit impact on child schooling

Microcredit affects child schooling in two ways:[76] one *beneficial* and one *adverse*. First, the *beneficial impact* is that household credit enables households to earn more; higher income will push up household consumption which further increases the demand for healthcare and child schooling (Armendariz & Morduch, 2005, p. 201). The credit could be spent on schooling (school fees, textbooks, schooling materials, uniforms and other schooling expenditure) as well as on improving child nutrition and shortening their sickness time by allowing children to take medicines promptly. As a result, the spending helps keep children at school. Similarly, Maldonado and Gonzalez-Vega (2008, p. 2,441) classify this channel of effect as "positive", and name this effect "income effect". The credit helps generate household income (positive impact) and then positively influences the demand for education. Moreover, education is a normal good, and thus it has a positive income-effect. As a result, an increase in education spending will positively affect child schooling. Therefore, access to credit allows households to smooth their consumption and then improve their decisions in favour of more education for their children (Maldonado, Gonzalez-Vega & Romeo, 2002, p. 29).

Inadequate schooling, a situation when children are required to drop out of schools to help their parents or to cut down household spending, is often attributed to lack of access to credit (Dehejia & Gatti, 2002; Edmonds, 2006; Jacoby & Skoufias, 1997; Ranjan, 2001). Households facing adverse shocks and having insufficient access to credit may withdraw children from school to reduce household expenditure and send children to work in order to smooth household consumption (Jacoby & Skoufias, 1997; Kurosaki, 2002). On the other hand, when households are able to borrow adequately at reasonable interest rates, they may not need child labour; then children may stay at schools longer. For example, according to CGAP(2003), there appears to be a large differential in child schooling between two groups of borrowers and non-borrowers in

[76] Generally, loans to the poor are often small so the terms "household credit" and "microcredit" are used interchangeably in this chapter.

Bangladesh; almost all girls of Grameen Bank borrowers have some years of schooling, whereas only 60% of non-borrowers' girls have some years of education. For boys, 81% and 54% respectively for borrowers and non-borrowers households have some schooling. Many other studies show that compared to non-clients of microfinance, enrolment rates and years of schooling are improved for microfinance clients' children after joining microfinance programs (Barnes, 2001; Chen & Snodgrass, 2001; Morduch, 1998; Pitt & Khandker, 1998).

The *second* way in which microcredit affects child schooling is a *child labour* or *adverse* effect. Borrowed money is spent on family businesses, which lead to an increase in household employment. This would undermine children's schooling because children have to replace their mothers in caring for their younger siblings, in looking after animals, and in doing housework and farming (Maldonado & Gonzalez-Vega, 2008, p. 2,441). Consequently, children may encounter adverse effects of credit on schooling; children quit school immediately or reduce time for schooling. Consequently, their academic performance gradually worsens; children may repeat classes or find themselves discouraged from staying at school longer, and eventually drop out. Furthermore, child labour and schooling are exclusively parents' decisions (Edmonds, 2006); so when parents need more labour to increase family income and smooth consumption, they may pull their children out of school.

Moreover, the child labour effect could result from requirements of immediate loan repayment. Loans to the poor often have higher interest rates (except subsidised loans) and short-term repayment conditions, as discussed in Chapters 3 and 4. Borrowers therefore require high returns to pay high interest rates in a short period of time. To ensure repayment, poor borrowers may try to reduce their business costs by employing their own labour, including children, without wages. Consequently, children from borrowing households may be pulled out of school. For instance, Beegle, Dehijia and Gatti (2004) in a study on Vietnam find that households borrowing from higher interest rate sources were more likely to have child labour. They suggest that to increase child schooling requires facilitating access to credit with lower interest rates.

Empirical studies of credit impacts on child schooling provide mixed evidence on these two types of effect. Pitt and Khandker (1998) find that girl schooling increased when households borrowed from Grameen Bank, but when households borrowed from other microcredit programs no positive impacts on girl schooling were observed. In contrast, Hazarika and Sarangi (2008), in a study on rural Malawi, find that children are more likely to work rather than go to school if their households have borrowed. In the case of Bangladesh, Morduch (1998) finds no effect on child schooling. Similarly, in the same country Islam and Choe (2009) even detect significantly adverse impacts of microcredit on child schooling.

7.3 Analytical framework[77]

7.3.1 Estimation methodological issues

As noted in Chapter 5, the most difficult part of impact evaluations is to separate out the causal effect of credit from selection and reverse causation biases which are common to nearly all statistical evaluations (Armendariz & Morduch, 2005, 2010). For example, the longsighted and richer households often have easier access to credit and one has to ask whether household credit really affects the households' child schooling, or is it that the more education-motivated and richer parents simply are more likely to send their children to school as well as having easier access to credit. Therefore, there is a potential for selection bias here and for this reason the inference from estimated impacts on outcomes could be misleading.

In the literature on credit impact evaluation as discussed in Chapter 5, selection biases from non-random placement of credit and self-selection into credit participation by borrowers have received much attention since these may cause overestimates of impacts (Amin, Rai, & Topa, 2003). Apart from randomisation methods (e.g. Banerjee, Duflo, Glennerster, & Kinnan, 2009), other strategies and methods to reduce bias have been used, including treating new clients as a control group, examining discontinuities in client eligibility, potential or future clients and fixed effects (see Coleman, 1999, 2006; Islam, 2010; McKernan, 2002; Morduch, 1998; Mosley, 1997; Pitt & Khandker, 1998; Roodman & Morduch, 2009). As a variant on these non-random methods, a purposely selected sample is used here to try to reduce the bias. All the households in my sample are poor, with initial income per capita under VND6 million (about US$1 per day) which makes them eligible for preferred (low interest rate and easy loan conditions) credits from the government. Thus, the non-random placement of credit borrowing should not be seriously problematic. In addition, the selection bias may be reduced by controlling for household pre-treatment income and parents' education, as suggested by Mosley (1997).

Some studies on schooling employ Two Stage Least Squares (2SLS) or Instrumental Variables (IV) (e.g. Berman & Knowles, 1999; Maitra, 2003) to address

[77] Sample design and data collection are discussed in Chapter 1.

selection and reverse causation biases. Demographic and educational characteristics of household heads, their jobs, household composition, and physical characteristics of dwellings are used as instruments. However, none of the studies applied the rigorous test for weak instruments suggested by Stock and Yogo (2002). Although the studies applied the test for endogeneity, the test is not able to ensure whether the instruments are good enough. For IV models, testing weak instruments using Maximum Likelihood Estimation (MLE) models is crucial (Murray, 2006); thus, using weak IVs could lead to upward biases, and the IV or 2SLS estimates could be worse than estimates by conventional estimators which treat credit participation as exogenous. In the current data, good instruments which affect credit participation but not child schooling are not available, I therefore apply only conventional Probit and Negative Binomial (NB) models.[78]

7.3.2 Probit and Negative Binomial model

Two outcomes of child schooling are examined here: current enrolment and the education gap. Analysis of the current enrolment is conducted using the standard Probit model. However, one single indicator e.g. grade attainment or current enrolment does not represent fully children's schooling because it does not indicate how well children did at school or whether or not children were grade-repeated. The education gap enables capture of this information, and it also represents how well children did at school. So the education gap may better reflect longer-term effects, while the current enrolment may reflect the immediate effect. The education gap is expressed as follows:

$$\text{Education gap} = \text{expected years of schooling} - \text{actual years of schooling}$$

$$\text{Expected years of schooling} = \begin{cases} 0 & \text{if age} \leq 6 \\ (\text{age - 6}) & \text{if } 6 < \text{age} \leq 18 \\ 12 & \text{if age} > 18 \end{cases}$$

The education gap can take positive integers from 0 to 12, thus the outcome of education gap is Poisson distributed, and a count data model is appropriate.

The count data model is well established (Cameron & Trivedi, 1986; Greene, 2008; Hausman, Hall & Griliches, 1984; Patil, 1970; Winkelmann, 2008, amongst others). Tabulating data on the outcome (Y) is a simple strategy to see the outcome

[78] Some potential IVs such as distance to banks, pre-treatment income and assets are used to conduct weak IV test, and all proved to be weak instruments.

distribution (Appendix 7.2). The smaller is the mean, the higher the proportion of zeros, so zero observations are an important feature of count data (Cameron & Trivedi, 2009).

The Poisson model is: $$\mu = E(y|x) = \exp(x'\beta) \tag{7.1}$$

where Y denotes the outcome (occurrences), Y= 0, 1, 2, …., N, and y(t, t+Δt) denote the number of events/occurrences observed in the interval (t, t+Δt). Then the number of occurrences in an interval of a given length is Poisson distributed with the probability density as follows:

$$\Pr(Y = y) = e^{-\mu}.\mu^{y}/y! \quad \text{where} \quad y = 0, 1, 2, \ldots, N$$

Conditional mean and variance of Y equal μ or Var(Y) = E(Y)=μ. When controlling for some exogenous variables x, the parameter μ is now specified as follows:

$$\mu = \exp(x'\beta) \tag{7.2}$$

The Poisson model is based on two assumptions. The *first* assumption is that events occur independently over time. The *second* assumption (called equidispersion, the key assumption of this model) is the equality of conditional mean and variance of dependent variable Y. In reality, equidispersion is commonly violated since count data is often overdispersed, that is the conditional variance exceeds the conditional mean (Cameron & Trivedi, 2009, p. 556). The distribution often has a longer right tail and the variance-mean ratio exceeds one. The presence of unobserved heterogeneity is one of the most common reasons for the violation to the second assumption. The Negative Binomial (NB) model can be a solution to this problem.

The NB model has *Gamma* distribution:

$$\mu = \text{gamma}(\phi, v) \tag{7.3}$$

where ϕ is mean and v is a precision parameter.

$$E[\mu]=\phi \text{ and } Var(\mu) = [1/v].\phi^2$$

$$\Pr[Y = y] = \int \Pr[Y = y \mid \mu] f(\mu) d\mu \tag{7.4}$$

With mean of dependent variable E[Y] = ϕ = exp(Xβ), and

$$Var(Y) = \phi + (1/v).\phi^2 = E[Y] + (1/v).(E[Y])^2 = E[Y]\,[1 + (1/v).(E[Y])] \tag{7.5}$$

$$\text{Var}(Y)=E[Y].(1+\alpha.E[Y])$$

Because $\phi > 0$ and $v > 0$ then Var(Y) > E(Y), and thus the model allows for overdispersion.

The test for Poisson models is based on tests for alpha $\alpha = 0$ against $\alpha \neq 0$. The Wald test is used to test the H_0: Poisson (μ= E[Y]) against H_A: Negative binomial model with mean μ and variance $\mu(1+\alpha.\mu)$. These two different parameterisations (Poisson and NB) imply different assumptions about functional form of heteroscedasticity. In reality, the outcome distribution is commonly overdispersed so the second assumption of the Poisson model is violated. Therefore, the NB models are preferable to Poisson models. This is the case for my data on the education gap where we have a conditional mean of 1.145 and variance of 2.190 (Appendix 7.2).

7.3.3 Propensity Score Matching (PSM)

To corroborate the Probit and NB estimation findings, the PSM (propensity score matching) method is also used. PSM is able to reduce the bias in the conventional estimates since it only compares the treatment group's outcome with that of a similar control group. With PSM, matched comparison and treatment groups are similar in terms of propensity scores built on observable characteristics (Dehejia & Wahba, 1998, 2002).[79] To evaluate the impact of credit participation on child schooling, PSM compares the schooling outcomes of children from borrowing households to what they would have had if their families did not borrow. Children from non-borrowers (who have the same or similar characteristics, such as demographic and socio-economic conditions which affect both credit participation and child schooling) are assumed to have the same outcomes that borrowers' children would have had if their parents had not borrowed. These children from non-borrower households can be used to generate a control group. So, what we need to do is to first estimate the propensity scores for each borrowing and non-borrowing household using household-level data and then merge the scores with the child-level data. The child-level data with the scores enables us to estimate the average treatment effects on child schooling using the PSM method.

[79] Discussions on advantages, disadvantages, conditions to successful PSM application, and the appropriateness of PSM application to the current dataset can be found in Chapter 5.

7.4 Empirical results

7.4.1 Descriptive analysis

Figure 7.1: Enrolment rate by age and borrowing status

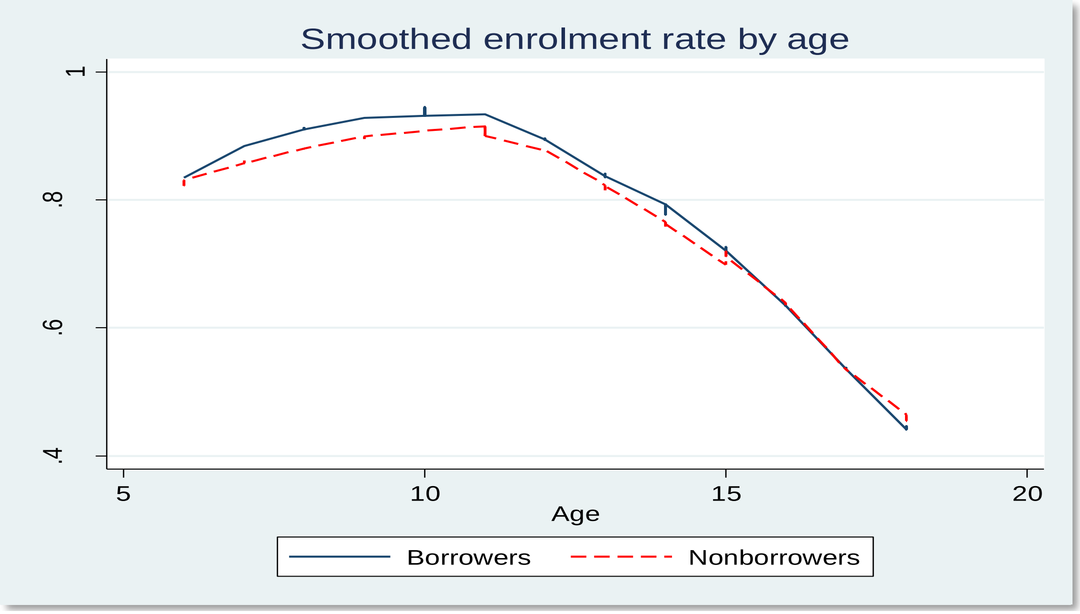
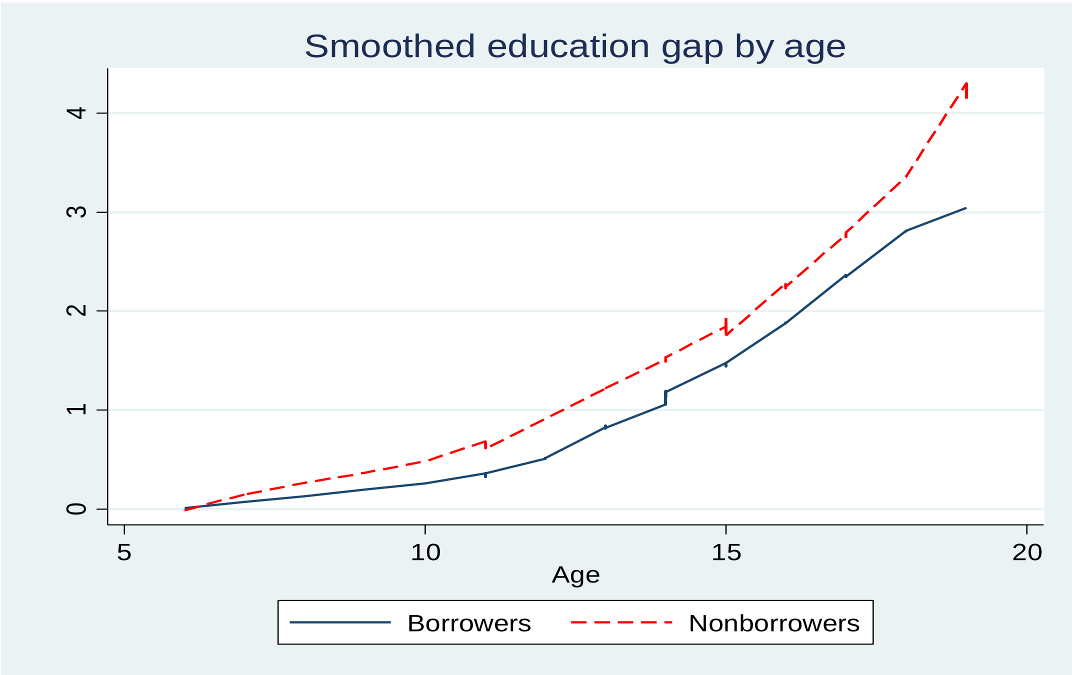


Figure 7.2: Education gap by age and by borrowing status



Unconditional mean differences in child schooling of child group aged 6-18 years old between borrowers and non-borrowers are presented in Table 7.1. Roughly, children from borrowing households are better off (higher enrolment and lower education gap) than their non-borrower counterparts. However, the difference is insignificant. The difference in current enrolment between borrowers' children and non-borrowers' children is not very obvious (Figure 7.1). The education gap may reflect outcomes of longer-term investment in schooling, since higher level education needs larger amounts of investment, and the poor are often both income-constrained and credit-constrained. Moreover, during the socio-economic reforms in Vietnam, cuts in public subsidies for higher education levels have pushed private education costs up. For these reasons, the education gap widens as child age increases (Figure 7.2).

7.4.2 Estimation results

Some current studies on schooling in Vietnam show that expenditure per capita (a proxy for household permanent income) is a good predictor of child schooling in Vietnam (Beegle, Dehijia, & Gatti, 2004; Behrman & Knowles, 1999). Accordingly, controlling for pre-treatment income, and assets as proxies for household wealth, is necessary. Furthermore, controlling for these initial variables can reduce selection bias as suggested by Mosley (1997) and can also avoid the problem of reverse causation bias that may occur if current income or expenditure is used.

7.4.2.1 Probit and Negative Binomial estimation results

Details of the education gap outcome distribution are presented in Appendix 7.2. The conditional mean is smaller than the variance so the distribution of the education gap is over-dispersed and has a longer right tail. Intuitively, the negative binomial models (NB) are appropriate in this case; however, to confirm this, I also run Poisson models and test for overdispersion, all the test results are statistically significant at the 1% level regardless of different alternative specifications;[80] thus, the Poisson models are strongly rejected in favour of the NB model. The appropriateness of applying NB model is confirmed by the Wald test results (test for α = zero) in Tables 7.3, 7.5, 7.7, and 7.8.[81] The test results imply that using NB improves the fit of the models, and the NB standard errors are smaller than the Poisson standard errors giving indicate more efficiency gains from NB models.

The reported results start with estimates for child schooling using maximum likelihood Probit for current enrolment and maximum likelihood NB for education gap. Next, I then consider whether the impacts for boys and girls are different. Following that, the impacts of different sources of credit are reported. Finally, I test whether or not the combination of credit and parental education (and with income) helps child schooling.

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[80] Applying *estat gof* after *poisson* command in Stata®

[81] Discussion on procedure for the test and choice of parameterisation is presented in Appendix 7.3. Alpha (α) can be interpreted as a measure of the variance of heterogeneity.

In each model, I include all children aged 6-18 years old. There are likely potential sources of biases that are between-household selection (i.e. which household sends children to school or their children stay longer at school), and within-household selection (i.e. which children are kept at school or receive more investment from their parents). The first problem can be addressed by controlling for household characteristics including household initial income, initial assets, parental education, credit participation, head's gender, number of children, distance to the nearest school, household dwelling locations, and especially household weights placed on each child.[82] For the second source of bias, I control further for child characteristics including child's gender, age and birth order. Schooling performance by children within a household may be influenced by child's IQ and parents' motivation (Bowles & Gentis, 2002). These factor effects can be captured by parental education, household income and assets. However, this leads to another potential problem that is the unobserved determinants of schooling, which are correlated across children within households. Thus, it may result in biased estimated standard errors (Deaton, 1997), and to correct the biased standard errors, robust clustered standard errors are estimated.

a) Maximum Likelihood Probit for current enrolment and Maximum Likelihood Negative Binomial model for education gap

The estimates in Tables 7.2 and 7.3 indicate that the probability of current enrolment and the size of the education gap are not significantly influenced by household credit. This finding is similar to Cameron and Heckman (1998) and Carneiro and Heckman (2002); these studies show that family background factors rather than short-term credit constraints determine education outcomes. The finding is also consistent with the relevant literature (Morduch, 1998; Manski, 1997; Kane, 1994) which indicates that credit participation or credit constraints do not significantly affect school attendance. In Chapter 5, I indicated that education expenditure was positively influenced by credit participation for households who already sent their children to schools, and it is likely that level of education expenditure is a current choice, while a decision regarding sending children to school and children's academic attainment reflects longer-term investments, and as such is affected by family background and economic conditions.

[82]Weights (scores) were estimated using PSM method, equal weight was placed on within-household children, but different weights were placed on between-household children. Weighted Probit and NB model estimates are not much different from those of the unweighted estimates since there are only about 1.05 children (aged 6 to 18) per household. The weighted estimates are reported in Appendix 7.4; 7.5, Appendix 7.6, and Appendix 7.7.

My finding agrees with Keane and Wolfin (2001) who point out that credit would have greater effects on consumption and labour supply than school enrolment.

Small loans are not an appropriate way of financing education investment. I observed from fieldwork that the loans of the poor in the peri-urban areas are often very short-termed, one year or less, especially loans from the informal credit sector; hence they are not used to support long-term investment in schooling. Moreover, in less developed countries, though many households borrowed, they were still credit-constrained because they were lent amounts smaller than those they demanded (Conning & Udry, 2005). Their loans were too small to finance long-term education investments,[83] particularly larger lump sums for tuition and registration fees for new schooling year (Mason & Rozelle, 1998). As a result, short and small loans affect only current education expenditure; bigger and longer-term loans are required to improve child enrolment and reduce education gap. This agrees with Islam (2010) who suggests that longer credit participation and larger loans could bring out benefits since it takes time to have effects.

Higher schooling fees and foregone earnings of older children would change roles of credit participation. Intuitively, one may think that the effects at upper levels of education would be higher than at lower levels. In order to examine the varying effects at different age groups, I run separate models for different age groups: 6-14 (primary & lower secondary school) and 15-18 (high school). Results are in Tables 7.2 and 7.3, columns 2 and 3, respectively. Estimates show no evidence of significant impacts of microcredit on enrolment rate at any level from 6 to 18 years old. This is also true for the education gap. The finding supports the previous discussion on trivial roles of small loans for child schooling.

b) The impacts of household credit on child schooling for boys and girls

In developing countries parents are biased in favour of boys over girls in human capital investment such as education. The literacy gender gaps are empirically examined to be very high in all developing regions (Wils & Goujon, 1998). To examine whether the trend is true in peri-urban areas in Vietnam, one could partition the sample into boy and girl groups and estimate two separate regressions. Small subsamples, however, may reduce the statistical significance of the estimates. I therefore employ an alternative approach to test the equality of credit variable coefficients between the two groups. I

[83] For my surveyed households, an average loan size for education is about US$220, and one of the smallest loan sizes of households compared to US$690 for other purposes (excluding consumption loans).

include interactions between each variable with a dummy of children's gender (boy=1) as additional variables. When the child gender dummy takes a value of zero (i.e. girls), all the interaction term coefficients equal zero, so the non-interacted coefficients provide effects for the girl group. On the other hand, child gender is one, the interacted term coefficients provide boy-girl difference estimates.

Tables 7.4 and 7.5 report the impacts of credit participation on female child schooling and the boy-girl difference in the impact. For the whole sample, female children from borrowing households have 9% more probability of current enrolment than same-sex children from non-borrowing households, but the effects are not statistically significant. For the younger group of primary and lower secondary education, the effect on girls' enrolment is in the same direction and statistically significant at the 5% level.[84] The effect difference between boys and girls is about (negative) 17% (i.e. the effect on boy schooling is about -8%), and it is strongly significant at the 1% level for the younger child group (Table 7.4). In short, when households borrowed, girls were better off but boys were worse off.

The NB model estimates (Table 7.5) provide similar results of the effects by gender. For the whole sample, household credit participation leads to a decline of 0.26 points in education gap for girls but leads to an increase of 0.37 points [0.37=0.11-(-0.26)] in education gap for boys. Roughly, this finding implies that the effect is heterogeneous across child gender: Girls benefit from household credit participation, but the credit adversely affects on boys' schooling.

Furthermore, girls' better academic performance is likely to help keep them at school longer and to receive more investment from their parents, that can be used to explain the positive impact on girls. Moreover, in the peri-urban areas in South Vietnam the traditional viewpoint of "valuing boys above girls or preferring boys to girls" has been increasingly weakened in recent times. Though the effects are not highly significant, my finding is contrary to Islam and Choe (2009) that microcredit in Bangladesh has negative impacts on both boys and girls, and the impact is (negative) stronger for girls than for boys. It is also contrary to the finding of positively significant effects of microcredit on child education, especially the impact for boys (Pitt & Khandker, 1998).

[84] Because of the small subsample of group aged 15 to 18, separate male and female groups are too small to run regressions.

c) The impacts of different sources of household credit

To evaluate whether different sources of credit matter in the impact on child schooling, I classify the borrowers into three groups: Households that borrowed from formal credit, households that borrowed from informal credit, and households that borrowed from both informal and formal credit.

The estimates in Tables 7.6 and 7.7 show that formal credit positively affects child schooling, whereas informal credit adversely affects child schooling; and the effects of both informal and formal credit are stronger for the high school children group. To see whether the effects of informal and formal credit are different, I conduct the parameter test for difference between coefficients of formal credit and informal credit, and the test reveals that the difference is statistically significant for both current enrolment (Table 7.6) and education gap (Table 7.7). The difference, however, mostly comes from the group of high school-aged children because older children can participate in the labour force when their parents need more labour, especially labour without wages, to reduce business costs in order to repay high interest rate loans from informal credit. This finding is similar to Beegle, Dehijia and Gatti (2004) who find that children from households who borrowed from informal credit sources may have to leave school because their parents may be too poor to afford schooling fees and may need extra labour for their family businesses. In addition, short-term and small loans from informal credit are not suitable for greater schooling costs, especially high schools.

d) The combination of credit with parental education (and with income) helps child schooling

Does the combination of credit and education help the poor? This question is motivated by the existing literature, which has shown that credit itself is not able to help the poor effectively. For example, using Bangladesh data Pitt and Khandker (1998) found that girl schooling increased when households borrowed from Gameen Bank, but when households borrowed from other microcredit programs positive impact on girl schooling was not observed. Intuitively, the combination of credit and manifestation of children's schooling benefits in the Grameen Bank group meetings, not microcredit itself, may account for the positive effects on children schooling.

Higher educated parents are often longsighted for their children's future livelihood, thus a combination of parental education and credit would accelerate the effects on child schooling. Therefore, to test whether parental education plays a role in accelerating the effect of credit usages in child education, I use an interaction term between credit and the highest parental education (of either husband or wife). The interaction term will capture the effect of parental education on child schooling within the borrowing household group. Moreover, families with more educated parents may have higher incomes; households with lower incomes among the poor may be too poor to afford child schooling costs, while less poor households are able to afford schooling if they have additional money from borrowing. Therefore, one may think that credit to richer households in the poor group may have stronger effects on child schooling.

I also use another interaction term between credit and pre-treatment income per capita to test whether among the borrower households, households with higher income have greater impacts on child schooling. The estimate results when estimating with inclusion of the interaction terms are presented in Table 7.8. The effects of both interaction terms are not statistically significant. The results suggest that amongst borrowing households children from higher educated and higher income parents also do not benefit from household credit for their schooling. In other words, there is no accelerator of parental education and initial income on the impact amongst poor borrowers because education of the poor parents is so low, only 5.5 years (achieved just primary school level) relative to that of parents in general in Vietnam - about 8.9 years of education (VHLSS, 2006).[85] Further, the return to schooling of lower education is very low (Doan & Gibson, 2009), hence the poor may not have been aware of educational benefits and may have had little motivation to increase their children's education.

7.4.2.2 Propensity Score Matching (PSM) estimation results

In order to corroborate the Probit and NB estimation results, I apply PSM methods to (i) binary treatment (household borrowed or not) and (ii) multiple treatment effect models. The matching methods (kernel and radius) are used for the whole sample and for a sub-sample of households having children aged 6-18 years old. According to Bryson et al (2002), controlling variables used to estimate scores should affect both credit participation and child schooling outcomes.[86] The variables include household head's gender, head's age, parental education, household head's marital status, number of children aged 6-18 years old, household members aged 18-60 years old, initial income per capita in logarithm, initial assets in logarithm, and household location dummies.

[85] This figure is estimated for general household head's education, if the highest parental education of either husband or wife is estimated, the years of education would be higher.
[86] For more detailed discussion on matching method, see Chapter 5.

The estimates are presented in Tables 7.9 and 7.10. *First*, the PSM estimation using the binary treatment effect shows that credit participation does not strongly affect child schooling (Table 7.9). Roughly, the PSM estimates are consistent with the Probit and NB model estimates.

Second, the multiple-treatment effect estimator in turn compares child schooling outcomes of informal borrowers and formal borrowers with that of the similar non-borrowers.[87] The estimates show that only formal credit affects the poor's child schooling, participation in formal credit improves the likelihood of enrolment and reduces the education gap (Table 7.10). Effect comparison between the formal and informal borrowing groups, however, would be inappropriate due to different counterfactuals of both these groups. Direct comparison in the last column of Table 7.10 is used to overcome the problem of incomparable counterfactuals. The informal credit with a smaller (accumulated) loan amount per household (about US$500 on average) and with short-terms is not sufficient to support child schooling, whereas formal credit (with about US$920) is beneficial to child schooling.[88] The multiple treatment effects analysis confirms the effects of household formal credit on child schooling. These findings also corroborate the Probit and NB model estimates.

7.5 Discussion and concluding remarks

This study evaluates the impact of household credit on child schooling of the poor in the peri-urban areas in Vietnam. The chapter delivers the following conclusions:

First, the small sized and short-term loans fail to help improve the poor's child schooling. *Second*, the effect of household credit varies across child gender. Girls are more likely to receive more education investment and stay longer at school. The finding contrasts with the existing literature on the differences in boy-girl schooling impacts in South Asia, which indicates that microcredit benefits boys more than girls or affects girls more adversely than boys. Furthermore, evidence of the traditional view of 'boys over girls', even though it is common in other similar developing countries, was not

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[87] The multiple treatments also help detect potential bias associated with unobservable characteristics in estimates of binary treatment effects (Lee, 2005, p. 119). If treatment level is increased (bigger loan size, here is the formal credit), then the effect will be stronger. Assume that our expectation is a positive effect, but the expectation is not confirmed by multiple ordered treatments, then the initial causal findings (from binary treatment) are questionable and may have been due to some unobserved attributes. On the other hand, if there is no hidden bias, the treatment effect of formal credit is higher than the effect of informal credit; in turn, the effect of informal credit is greater than the observed outcome for the non-borrowing group, controlling for the same set of covariates X_i.

[88] The average loan size is VND5,229 thousand (about USD317) and VND9,327 thousand (about USD566) for informal and formal credit respectively, since many households have more than one loans so the reported sizes of loan in the text are accumulated ones. Note that not all of these amounts are for education, but they are used for all purposes.

observed in this peri-urban area of HCMC, Vietnam. Girls' better schooling performance helps keep them at school longer and hence they receive more investment in education from their parents.

Third, a closer look at impacts of each credit source reveals that formal credit has brought beneficial effects to children's education, while informal credit has failed to do so. Consequently, to improve child schooling in the long term needs to ease access to formal credit for the poor. Otherwise, the poor will continue to rely on informal credit and will end up in debt and will then pull their children out of school. Consequently, informal credit may exacerbate poverty in the long term rather than help the poor out of poverty. The poor are both income and credit constrained, so government interventions such as facilitating formal credit access are needed (Caucutt & Lochner, 2005). The poor need a "big push" to break down the vicious circle of poverty.

Providing subsidies or tuition exemption to all children is an impossible solution in poor countries like Vietnam since it may pose a burden on the government budget. An alternative is to target subsidies to low-income household child schooling. In fact, the current tuition exemption policy in Vietnam is ineffective to help poor children because the tuition accounts for just less than one third of total education costs, and almost all school fee exemptions are for primary schools regardless of parental income levels. Only 1% of the tuition exemption value is for children from poor households and 4.3% is for ethnic minorities (Behrman & Knowles, 1999, p. 230). Therefore, expanding preferred loans or fully tuition exemption to the poor, as well as providing subsidies for textbooks, uniforms, study materials and other school fees is a further necessary policy to encourage poor children to go to school and keep them at school longer.

In Vietnam, the greater school expenditure, which is influenced by household budget constraints, may relate to obtaining higher quality schooling and better academic performance from participating in extra classes (Dang, 2007). Therefore, credit still has an important role in education investment. However, regulated tuition levels by the government could partly undermine the effects of credit on schooling.

TABLES

Table 7.1: Mean values of some key variables and t-values for equal means for the group of 6 to 18 years old children by borrowing status

Variables	Borrowers		Non-borrowers		*t*-value
	Mean	Std	Mean	Std	
Head's gender (male=1)	0.528	0.500	0.606	0.491	1.43
Parents' highest education (years)	5.551	3.333	5.452	3.585	0.26
Head married (yes=1)	0.723	0.448	0.730	0.446	0.16
Head's age (years)	50.501	13.762	57.625	15.300	4.30**
Household size (persons)	6.087	2.743	6.433	3.335	0.97
Younger siblings under 6 years (yes=1)	0.280	0.449	0.240	0.429	0.82
Children from 6 to 18 years old	1.942	0.963	2.096	1.187	1.22
Members from 18 to 60 years old	3.325	1.670	3.202	2.002	0.57
Members older than 60 (yes=1)	0.293	0.456	0.529	0.502	4.33**
Distance to nearest aged-range school	1.247	1.481	1.298	1.451	0.31
Child's gender (male=1)	0.451	0.498	0.5481	0.500	1.75+
Child's age (years)	12.823	3.708	13.096	3.693	0.67
Value of durable assets acquired over 24 months, land and house (in log)	13.149	1.180	12.702	1.929	2.25*
Pre-survey income per capita (in log)	8.115	0.234	8.102	0.389	0.32
Enrolment rate (children aged 6-18)	0.784	0.413	0.760	0.429	0.51
Education gap[(a)] (children aged 6-18)	1.061	2.216	1.346	2.392	1.10
Enrolment rate (children aged 6-14)	0.917	0.276	0.911	0.288	0.16
Education gap (children aged 6-14)	0.265	0.750	0.429	0.951	1.20
Enrolment rate (children aged 15-18)	0.577	0.496	0.583	0.498	0.08
Education gap (children aged 15-18)	2.289	3.028	2.417	3.052	0.25

Notes: t-value statistically significant at 10% (+), 5% (*), and 1% (**). (a) The education gap here is a real gap between the expected years of education minus the actual children's years of education.

Table 7.2: Marginal effects of credit on current enrolment (Probit model)

Explanatory variables	Whole sample	Children aged 6-14	Children aged 15-18
Credit participation (yes=1)	-0.0032	-0.0139	0.0223
	(0.08)	(0.66)	(0.23)
Pre-treatment income capita in log	0.0575	0.0781	-0.1928
	(0.97)	(2.48)*	(1.30)
Pre-treatment asset in log	0.0127	0.0023	0.0066
	(1.03)	(0.42)	(0.19)
Highest parental education (year)	0.0256	0.0125	0.0424
	(4.08)**	(3.84)**	(2.96)**
Household head's gender (male=1)	0.0231	0.0042	0.0453
	(0.62)	(0.19)	(0.54)
Number of children aged 6-18	-0.0656	-0.0303	-0.1343
	(3.71)**	(2.79)**	(3.31)**
Labour force[(a)]	-0.0061	-0.0000	0.0041
	(0.69)	(0.01)	(0.17)
Child's gender (male=1)	-0.0892	0.0052	-0.2940
	(2.53)*	(0.30)	(3.64)**
Firstborn child (yes =1)	0.0334	-0.0305	0.1980
	(0.87)	(1.19)	(2.30)*
Child's age	0.1801	0.0907	-0.1884
	(4.87)**	(2.76)**	(4.13)**
Child's age squared	-0.0090	-0.0044	
	(5.79)**	(2.71)**	
Distance to the nearest school[(b)]	-0.0019	-0.0138	0.0364
	(0.13)	(0.98)	(1.01)
Observations	483	286	197
Pseudo R-squared	0.30	0.24	0.22
Wald χ^2 (all coefficients=0)	111.31	37.17	50.18
Prob > χ^2	0.000	0.001	0.000
Predicted probabilities at x-bar	0.858	0.965	0.596

*Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Column 1 is for the whole sample; Column 2 is for a sub-sample of children aged 6 to 14 (primary and lower secondary school ages); Column 3 is for a sub-sample of children aged 15 to 18 (high school ages). [(a)]The number of household members aged 18-60 as a proxy for labour force. [(b)]The distance is regarded to ages at different educational levels e.g. it is the distance to the nearest primary school if 6 ≤ age ≤ 10; the distance to the nearest lower secondary school if 11 ≤ age ≤14; the distance to the nearest upper secondary or high school if 15 ≤ age ≤18. All the models were controlled for location dummies.*

Table 7.3: Negative Binomial Regression (NB2) for credit impact on education gap

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Credit participation	-0.0313	0.0290	0.0168
(yes=1)	(0.15)	(0.09)	(0.07)
Pre-treatment income	-0.2516	-0.7769	0.2454
capita in logarithm	(0.85)	(2.13)*	(0.71)
Pre-treatment asset in	-0.0763	-0.0907	-0.0350
logarithm	(1.20)	(1.02)	(0.49)
Highest parental education	-0.0818	-0.1523	-0.0485
(years)	(2.46)*	(2.50)*	(1.33)
Household head's gender	-0.0348	-0.2499	0.1293
(male=1)	(0.21)	(0.75)	(0.68)
Number of children aged	0.2046	0.2772	0.2106
6-18 years old	(2.65)**	(1.75)+	(2.13)*
Labour force	0.0252	0.0427	-0.0317
	(0.50)	(0.52)	(0.60)
Child's gender (male=1)	0.4080	0.3439	0.4509
	(2.41)*	(1.18)	(2.20)*
Firstborn child (yes =1)	0.0351	0.1317	-0.1242
	(0.18)	(0.36)	(0.57)
Child's age	0.3411	0.2704	0.3566
	(9.17)**	(4.78)**	(3.09)**
Distance to the nearest	-1.1115	-1.5309	-1.2794
school	(2.99)**	(2.77)**	(3.14)**
Constant	-1.8093	3.9100	-6.6078
	(0.68)	(1.45)	(1.63)
Observations	483	286	197
Wald χ^2 (all coefficients=0)	222.96	79.24	40.79
Prob > χ^2	0.000	0.000	0.000
Alpha $\alpha^{(a)}$	1.3868	1.2798	1.2193
	(5.85)**	(1.91)+	(5.45)**

*[(a)]The alpha parameter, highly significant, means that the Negative Binomial regression is an appropriate approach. Model in column 2, the test of α=0 is accepted at the 5% level, either the Poisson or NB can be applied in this case. The estimated results by the NB and Poisson estimators are similar. Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Column 1 is for the whole sample; Column 2 is for a sub-sample of children aged 6 to 14 (primary and lower secondary school ages); Column 3 is for a sub-sample of children aged 15 to 18 (high school ages). All the models were controlled for location dummies.*

Table 7.4: Marginal effect of credit on current enrolment by gender (Probit)

Explanatory variables	Children aged 6-18		Children aged 6-14	
	Girl	Boy-girl difference[(a)]	Girl	Boy-girl difference[(b)]
Credit participation (yes=1)	0.0915	-0.1712	0.0496	-0.2276
	(1.41)	(1.93)+	(2.37)*	(3.54)**
Pre-treatment income capita in logarithm	-0.0405	0.1207	0.0164	0.0201
	(0.57)	(1.11)	(1.33)	(1.16)
Pre-treatment asset in logarithm	0.0458	-0.0562	0.0033	-0.0078
	(2.74)**	(2.53)*	(1.57)	(1.92)+
Highest parents' education	0.0300	-0.0069	0.0027	0.0036
	(3.76)**	(0.58)	(1.93)+	(1.48)
Household head's gender (male=1)	0.0473	-0.1011	0.0216	-0.1073
	(0.92)	(1.26)	(1.81)+	(2.42)*
Number of children from 6 to 18 years old	-0.0366	-0.0593	-0.0030	-0.0128
	(1.60)	(1.72)+	(0.62)	(1.96)+
Labour force	-0.0115	0.0117	-0.0003	0.0005
	(0.92)	(0.69)	(0.19)	(0.19)
Firstborn child (yes=1)	0.0759	-0.0988	-0.0011	-0.0200
	(1.49)	(1.13)	(0.11)	(0.82)
Child's age	0.2117	-0.0642	0.0386	-0.0232
	(4.45)**	(0.92)	(3.35)**	(1.22)
Child's age squared	-0.0098	0.0018	-0.0018	0.0011
	(4.99)**	(0.63)	(3.19)**	(1.15)
Distance to the nearest school	0.0091	-0.0214	0.0000	-0.0072
	(0.45)	(0.78)	(0.01)	(0.97)
Pseudo R-squared	0.35		0.39	
Wald χ^2 (all coefficients =0)	135.74		84.70	
Prob > χ^2	0.000		0.000	
Observations	483		286	

*Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; [(a)] & [(b)] are coefficients of interaction terms between the explanatory variables and child's gender dummy (boy =1). All the models were controlled for location dummies.*

Table 7.5: Impact of credit participation on education gap by gender (NB model)

Explanatory variables	Aged 6-18		Aged 6-14	
	Girl	Boy-girl difference(a)	Girl	Boy-girl difference(b)
Credit participation (yes=1)	-0.2616	0.3726	-0.7496	1.1840
	(0.93)	(0.94)	(1.64)+	(1.98)*
Pre-treatment income capita in logarithm	-0.2196	0.0736	-0.7754	0.2298
	(0.49)	(0.12)	(1.04)	(0.26)
Pre-treatment asset In logarithm	-0.2109	0.2057	-0.1121	0.1425
	(2.06)*	(1.69)+	(1.08)	(0.96)
Highest parent's education	-0.1419	0.1023	-0.2420	0.1681
	(3.14)**	(1.63)	(2.60)**	(1.36)
Household head's gender (male=1)	-0.1436	0.2616	-0.4496	0.5953
	(0.54)	(0.76)	(0.83)	(0.90)
Number of children from 6 to 18 years old	0.1271	0.1454	-0.1596	0.6861
	(1.10)	(0.96)	(0.76)	(2.27)*
Labour force	0.0379	-0.0254	0.0363	0.0741
	(0.47)	(0.25)	(0.39)	(0.52)
Firstborn child (yes=1)	0.0245	0.0858	0.1971	-0.0872
	(0.08)	(0.21)	(0.41)	(0.13)
Child's age	0.3491	0.0024	0.3610	-0.1924
	(6.37)**	(0.03)	(3.25)**	(1.56)
Distance to the nearest School	0.1700	-0.0995	0.1092	0.0144
	(1.33)	(0.67)	(0.31)	(0.04)
Constant		-0.1659		4.2791
		(0.04)		(0.73)
Alpha (α)	1.3918		0.6967	
	(5.96)**		(1.57)	
Wald χ^2 (all coefficients=0)	292.74		131.02	
Prob > χ^2	0.0000		0.0000	
Observations	483		286	

*Robust z statistics in parentheses; + significant at 10%; * significant at 5%; and ** significant at 1%. (a) & (b) are coefficients of interaction terms between the explanatory variables and child's gender dummy (boy =1). All the models were controlled for location dummies.*

Table 7.6: Marginal effects on enrolment status by types of credit (probit model)

Explanatory variables	Whole sample	Children aged 6-14	Children aged 15-18
Informal credit (yes=1)	-0.0639	-0.0002	-0.1461
	(1.25)	(0.01)	(1.19)
Both sources of credit (yes=1)	-0.0160	-0.0409	0.0037
	(0.33)	(1.33)	(0.03)
Formal credit (yes=1)	0.0637	-0.0121	0.1959
	(1.25)	(0.39)	(1.70)+
Pre-treatment income capita in logarithm	0.0634	0.0767	-0.1633
	(1.10)	(2.72)**	(1.13)
Pre-treatment asset in Logarithm	0.0155	0.0020	0.0125
	(1.22)	(0.38)	(0.36)
Highest parental education	0.0240	0.0135	0.0417
	(3.98)**	(4.53)**	(2.98)**
Household head's gender (male=1)	0.0184	-0.0050	0.0339
	(0.50)	(0.26)	(0.39)
Number of children aged 6-18	-0.0613	-0.0269	-0.1227
	(3.48)**	(2.65)**	(3.02)**
Labour force	-0.0080	0.0014	-0.0069
	(0.89)	(0.35)	(0.28)
Child's gender (boy=1)	-0.0898	0.0079	-0.2883
	(2.58)**	(0.46)	(3.53)**
First born child (yes=1)	0.0318	-0.0265	0.1842
	(0.84)	(1.12)	(2.11)*
Child's age	0.1774	0.0860	-0.1754
	(4.86)**	(2.82)**	(3.82)**
Child's age squared	-0.0088	-0.0041	
	(5.77)**	(2.76)**	
Distance to the nearest school	0.1116	0.0362	0.2535
	(1.96)+	(1.48)	(1.68)+
H_0: $\beta_{informal} = \beta_{formal}$ (P-value)	0.019*	0.672	0.007**
Pseudo R-squared	0.31	0.25	0.25
Wald χ^2 (all coeffs=0)	110.89	47.94	57.79
Prob > χ^2	0.0000	0.0000	0.0000
Observations	483	286	197

*Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; the reference group for credit types is non-borrowers. All the models were controlled for location dummies.*

Table 7.7: Impact on education gap by type of credit (NB model)

Explanatory variables	Whole sample	Children aged 6-14	Children aged 15-18
Informal credit (yes=1)	0.1006	-0.1181	0.2852
	(0.44)	(0.28)	(1.02)
Both sources of credit (yes=1)	0.0995	0.2099	0.1184
	(0.40)	(0.52)	(0.44)
Formal credit (yes=1)	-0.3411	0.0239	-0.3897
	(1.25)	(0.06)	(1.25)
Pre-treatment income capita in logarithm	-0.2835	-0.8128	0.1778
	(0.99)	(2.21)*	(0.53)
Pre-treatment asset in logarithm	-0.0797	-0.0842	-0.0353
	(1.27)	(0.90)	(0.52)
Highest parental education (years)	-0.0788	-0.1580	-0.0455
	(2.50)*	(2.58)*	(1.32)
Household head's gender (male=1)	0.0062	-0.2003	0.1571
	(0.04)	(0.61)	(0.79)
Number of children aged 6 to 18	0.1995	0.2659	0.1920
	(2.58)**	(1.69)+	(1.97)*
Labour force	0.0281	0.0271	-0.0069
	(0.58)	(0.34)	(0.13)
Child's gender (boy=1)	0.4206	0.2950	0.4364
	(2.53)*	(1.04)	(2.17)*
First born (yes=1)	0.0496	0.1236	-0.0912
	(0.26)	(0.34)	(0.42)
Child's age	0.3346	0.2691	0.3016
	(9.06)**	(4.76)**	(2.62)**
Distance to the nearest school	-1.0455	-1.4828	-1.1493
	(2.82)**	(2.65)**	(2.85)**
Constant	-1.4565	4.2060	-5.2948
	(0.57)	(1.50)	(1.35)
H_0: $\beta_{informal} = \beta_{formal}$ (P-value)	0.084+	0.730	0.035*
Alpha (α)	1.3488	1.2806	1.1611
	(5.8)**	(1.91)+	(5.3)**
Wald χ^2 (all coefficients=0)	231.47	88.34	50.89
Prob > χ^2	0.0000	0.0000	0.0000
Observations	483	286	197

*Notes: Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Model in column 2, the test of α=0 is accepted at the 5% level, either the Poisson or NB can be applied in this case. The estimated results by the NB and Poisson estimators are similar. The reference group for credit types is non-borrowers. All the models were controlled for location dummies.*

Table 7.8: Effect of interaction terms between credit and parental education, and credit and household income

Explanatory variables	dprobit model[(a)]	NB model
Credit participation (yes =1)	0.7214	-1.2088
	(0.55)	(0.27)
Pre-treatment income capita in logarithm	0.0891	-0.2832
	(1.13)	(0.81)
Pre-treatment asset in logarithm	0.0130	-0.0638
	(1.07)	(0.96)
Highest parental education	0.0228	-0.1475
	(2.00)*	(2.35)*
Credit participation*income per capita	-0.0674	0.0849
	(0.58)	(0.16)
Credit participation*highest	0.0035	0.0918
parental education	(0.26)	(1.26)
Household head's gender (male=1)	0.0246	-0.0377
	(0.66)	(0.22)
Number of children from aged 6-18	-0.0669	0.2130
	(3.71)**	(2.69)**
Labour force	-0.0058	0.0258
	(0.65)	(0.52)
Child's gender (male=1)	-0.0894	0.3966
	(2.54)*	(2.37)*
First born child (yes =1)	0.0351	0.0382
	(0.91)	(0.20)
Child's age	0.1809	0.3453
	(4.87)**	(9.50)**
Child's age squared	-0.0090	
	(5.79)**	
Distance to the nearest school	-0.0010	0.1028
	(0.07)	(1.64)+
Constant		-1.4549
		(0.50)
Observations	483	483
Wald χ^2 (all coefficients=0)	114.17	224.50
Prob > χ^2	0.0000	0.0000
Pseudo R-squared	0.30	
Alpha (α)		1.3849
		(5.9)**

*Note: Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; [(a)]dprobit model estimates marginal effects. All the models were controlled for location dummies.*

Table 7.9: The Average Treatment Effects using matching estimators

Propensity score estimation stage	Outcome of schooling	Treated/ controls	Kernel matching	Radius matching
A subsample (households with children aged 6-18)	Current Enrolment	370/84	0.017	0.031
			(0.054)	(0.061)
	Education Gap (year)	370/84	-0.167	-0.194
			(0.297)	(0.300)
Whole sample	Current Enrolment	379/98	0.010	0.010
			(0.052)	(0.054)
	Education Gap (year)	379/98	-0.146	-0.138
			(0.282)	(0.292)

Notes: Bootstrapped standard errors in parentheses with 1000 repetitions, statistically significant at 10% (+); 5%(*); 1%(**). Only few households (10 households) have more than or equal 4 children aged 6-18, to get balanced easier I group them into households having 4 kids. Controlling variables in the propensity score estimation (propensity score estimation with household level data): Head's gender, head's age, parental highest education, marital status, children aged 6-18, members aged 18-60, initial income in log, initial assets in logarithm, ward dummies.

Table 7.10: The average treatment effects using matching estimators with whole sample in propensity score estimation

Outcome of schooling	Informal credit vs Non-borrowers		Formal credit vs Non-borrowers		Formal vs Informal
	ATTK	ATTR	ATTK	ATTR	ATTR
Current Enrolment	-0.024	-0.025	0.140	0.105	0.129
	(0.072)	(0.075)	(0.058)*	(0.052)*	(0.054)*
Education Gap (year)	0.023	0.043	-0.746	-0.665	-0.745
	(0.395)	(0.379)	(0.300)*	(0.293)*	(0.273)**

*Notes: Bootstrapped standard errors in parentheses with 1000 replications, statistically significant at 10% (+); 5%(*); 1%(**). Controlling variables in the propensity score estimation: Head's gender, head's age, highest parental education, marital status, ward dummies, number of children aged 6-18, number of members aged 18-60, initial income in logarithm, initial assets in logarithm, and head's age*education.*

APPENDICES

Appendix 7.1: Smoothed child enrolment ratio and education gap by age

Child Age	Enrolment rate (%)		Education gap (years)	
	Borrowers	Non-borrowers	Borrowers	Non-borrowers
6	83.3	82.2	0.01	0.00
7	87.9	85.6	0.07	0.13
8	91.3	88.1	0.13	0.26
9	93.3	89.9	0.19	0.37
10	94.4	91.6	0.26	0.48
11	93.4	91.5	0.33	0.62
12	89.4	87.9	0.50	0.91
13	85.0	83.4	0.81	1.23
14	79.5	77.8	1.07	1.52
15	72.5	71.7	1.44	1.77
16	63.5	63.9	1.89	2.23
17	53.6	53.4	2.40	2.75
18	44.6	46.2	2.81	3.36

Notes: Bandwidth (a smoothing parameter) = 0.9 is chosen in the Lowess (locally weighted scatter-plot smoothing estimator) command in Stata®. This information is used to graph Figure 7.1 and Figure 7.2.

Appendix 7.2: Mean and variance of education gap for children aged 6-18

Variable	Observations	Mean	Variance	Std.Dev	Min	Max
Unconditional	483	1.122	5.087	2.255	0.000	12
Conditional	483	1.145	2.190	1.480	0.019	12

Source: estimation from the author's survey

Tabulation of education gap for children from 6 to 18 years old

Education gap	Frequency	Percent	Cumulative
0	31	6.42	6.42
1	284	58.80	65.22
2	64	13.25	78.47
3	32	6.63	85.09
4	17	3.52	88.61
5	14	2.90	91.51
6	8	1.66	93.17
7	12	2.48	95.65
8	4	0.83	96.48
9	1	0.21	96.69
10	8	1.66	98.34
11	3	0.62	98.96
12	5	1.04	100.00
Total	483	100.00	100.00

Source: Estimation from the author's survey

Appendix 7.3: Choice of Negative Binomial Models

NB models fit two different parameterisations of the NB model: Negbin I or NB_1: (Var(Y)=(1+ δ)E[Y] - a linear variance function), and Negbin II or NB_2: (Var(Y)=E[Y].(1+α.E[Y]) - a version with quadratic variance. The NB_2 has dispersion (ratio of variance/mean) for the i^{th} observation equal to 1+α.E[Y_i] i.e., the dispersion is a function of the expected mean of the counts for the j^{th} observation: E[Y_i]. The alternative parameterisation, NB_1, has dispersion equal to 1 + δ; i.e. it is a constant for all observations. If alpha α = 0 (or delta δ =0) corresponds to dispersion = 1, thus it is simply a Poisson model. One may want to fit both parameterisations NB_1 and NB_2, and choosing either of them rely on larger (least negative) log pseudo likelihood. In most cases, however, both models will yield similar results, and the parameterisations will not significantly differ from one another. Thus, the choice of parameterisation is not important (Cameron & Trivedi, 2009).

A common approach to deal with the overdispersion for count data is to use the generalised linear model including NB (Hoef & Boveng, 2007) because the overdispersion parameter can vary across individuals so some variables can affect the location and scale parameters of the distribution, therefore, the generalised NB model which allows the different effects of different variables on the location and the scale of the distribution (Cameron & Trivedi, 2009). In my case, I compare the regression statistics, e.g. Log pseudo likelihood, and see that both NB_2 and generalised NB produced identical statistics. As a result, I apply only NB_2 in the current research.

Appendix 7.4: Marginal effects of credit on current enrolment (weighted Probit estimates)

Explanatory variables	Whole sample	Children aged 6-14	Children aged 15-18
Credit participation (yes=1)	-0.0028	-0.0116	0.0154
	(0.07)	(0.51)	(0.16)
Pre-treatment income capita in logarithm	0.0142	0.0583	-0.2567
	(0.21)	(1.54)	(1.42)
Pre-treatment asset in logarithm	0.0119	0.0015	0.0095
	(0.95)	(0.27)	(0.27)
Highest parental education (year)	0.0261	0.0127	0.0439
	(4.06)**	(3.68)**	(3.02)**
Household head's gender (male=1)	0.0341	0.0123	0.0529
	(0.91)	(0.52)	(0.63)
Number of children aged 6-18	-0.0674	-0.0306	-0.1419
	(3.75)**	(2.67)**	(3.46)**
Labour force[(a)]	-0.0060	0.0007	0.0025
	(0.67)	(0.16)	(0.10)
Child's gender (male=1)	-0.0900	0.0068	-0.3028
	(2.47)*	(0.36)	(3.69)**
Firstborn child (yes =1)	0.0228	-0.0331	0.1872
	(0.58)	(1.23)	(2.15)*
Child's age	0.1791	0.0944	-0.1939
	(4.69)**	(2.74)**	(4.12)**
Child's age squared	-0.0090	-0.0046	
	(5.64)**	(2.71)**	
Distance to the nearest school[(b)]	0.0007	-0.0141	0.0366
	(0.05)	(0.96)	(1.00)
Observations	483	286	197
Pseudo R-squared	0.30	0.21	0.23
Wald χ^2 (all coefficients=0)	112.54	33.01	51.58
Prob > χ^2	0.000	0.001	0.000
Predicted probabilities at x-bar	0.86	0.96	0.59

*Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Column 1 is for the whole sample; Column 2 is for a sub-sample of children aged 6 to 14 (primary and lower secondary school ages); Column 3 is for a sub-sample of children aged 15 to 18 (high school ages). [(a)]The number of household members aged 18-60 as a proxy for labour force. [(b)]The distance is regarded to ages at different educational levels e.g. it is the distance to the nearest primary school if $6 \leq$ age ≤ 10; the distance to the nearest lower secondary school if $11 \leq$ age ≤ 14; the distance to the nearest upper secondary or high school if $15 \leq$ age ≤ 18. All the models were controlled for location dummies.*

Appendix 7.5: Credit impact on education gap (weighted NB estimates)

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Credit participation	-0.0173	0.0481	0.0111
(yes=1)	(0.08)	(0.14)	(0.05)
Pre-treatment income	-0.0887	-0.8237	0.3785
capita in logarithm	(0.25)	(1.64)	(0.96)
Pre-treatment asset	-0.0717	-0.0949	-0.0308
in logarithm	(1.07)	(0.93)	(0.42)
Highest parental education	-0.0832	-0.1550	-0.0504
(years)	(2.48)*	(2.47)*	(1.38)
Household head's gender	-0.0915	-0.3405	0.0872
(male=1)	(0.54)	(1.03)	(0.46)
Number of children	0.2021	0.2458	0.2040
aged 6-18	(2.57)*	(1.54)	(2.06)*
Labour force	0.0253	0.0374	-0.0243
	(0.50)	(0.46)	(0.46)
Child's gender (male=1)	0.3967	0.3653	0.4309
	(2.32)*	(1.22)	(2.11)*
Firstborn child (yes =1)	0.1191	0.1748	-0.0300
	(0.61)	(0.47)	(0.14)
Child's age	0.3501	0.2699	0.3557
	(8.77)**	(4.56)**	(2.99)**
Distance to the nearest	-1.0308	-1.5100	-1.1781
school	(2.63)**	(2.63)**	(2.87)**
Constant	-3.3714	4.4675	-7.8268
	(1.01)	(1.09)	(1.70)+
Observations	483	286	197
Wald χ^2 (all coefficients=0)	225.64	58.02	41.56
Prob > χ^2	0.000	0.000	0.000
Alpha $\alpha^{(a)}$	1.3862	1.5292	1.3862
	(5.71)**	(2.14)*	(5.71)**

*[(a)] The alpha parameter, highly significant, means that the Negative Binomial regression is an appropriate approach. Model in column 2, the test of α=0 is accepted at the 5% level, either the Poisson or NB can be applied in this case. The estimated results by the NB and Poisson estimators are similar. Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Column 1 is for the whole sample; Column 2 is for a sub-sample of children aged 6 to 14 (primary and lower secondary school ages); Column 3 is for a sub-sample of children aged 15 to 18 (high school ages). All the models were controlled for location dummies.*

Appendix 7.6: Marginal effects on enrolment status by types of credit (weighted probit estimates)

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Informal credit	-0.0590	0.0029	-0.1390
	(1.14)	(0.11)	(1.13)
Both sources of credit	-0.0161	-0.0344	-0.0093
	(0.33)	(1.12)	(0.08)
Formal credit	0.0662	-0.0093	0.1909
	(1.28)	(0.29)	(1.63)
Pre-treatment income capita in logarithm	0.0218	0.0610	-0.2256
	(0.33)	(1.83)+	(1.28)
Pre-treatment asset in log	0.0142	0.0014	0.0151
	(1.12)	(0.26)	(0.42)
Highest parental education	0.0245	0.0137	0.0434
	(3.99)**	(4.36)**	(3.07)**
Household head's gender (male=1)	0.0277	0.0024	0.0379
	(0.74)	(0.12)	(0.43)
Number of children aged 6-18	-0.0630	-0.0272	-0.1302
	(3.51)**	(2.50)*	(3.15)**
Labour force	-0.0080	0.0021	-0.0083
	(0.89)	(0.50)	(0.33)
Child's gender (boy=1)	-0.0895	0.0095	-0.2953
	(2.50)*	(0.52)	(3.57)**
First born child (yes=1)	0.0211	-0.0292	0.1710
	(0.54)	(1.17)	(1.92)+
Child's age	0.1761	0.0896	-0.1806
	(4.68)**	(2.79)**	(3.83)**
Child's age squared	-0.0089	-0.0043	
	(5.62)**	(2.76)**	
Distance to the nearest school	0.1062	0.0335	0.2395
	(1.78)+	(1.23)	(1.53)
H_0: $\beta_{informal} = \beta_{formal}$ (P-value)	0.024*	0.6633	0.012*
Pseudo R-squared	0.31	0.22	0.25
Wald χ^2 (all coeffs=0)	112.64	43.91	58.68
Prob > χ^2	0.0000	0.0000	0.0000
Observations	483	286	197

*Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; All the models were controlled for location dummies.*

Appendix 7.7: Impact on education gap by type of credit (weighted NB estimates)

Explanatory variables	Whole sample	Child aged 6-14	Child aged 15-18
Informal credit	0.0893	-0.1129	0.2458
	(0.38)	(0.26)	(0.91)
Both sources of credit	0.1084	0.2479	0.1147
	(0.43)	(0.60)	(0.44)
Formal credit	-0.3230	0.0149	-0.3755
	(1.16)	(0.03)	(1.21)
Pre-treatment income capita in logarithm	-0.1383	-0.9054	0.3026
	(0.40)	(1.75)+	(0.80)
Pre-treatment asset in logarithm	-0.0741	-0.0899	-0.0312
	(1.14)	(0.84)	(0.45)
Highest parental education (years)	-0.0812	-0.1620	-0.0484
	(2.55)*	(2.57)*	(1.42)
Household head's gender (male=1)	-0.0454	-0.2746	0.1184
	(0.26)	(0.84)	(0.60)
Number of children aged 6-18	0.1962	0.2303	0.1853
	(2.50)*	(1.45)	(1.90)+
Labour force	0.0274	0.0196	-0.0024
	(0.57)	(0.25)	(0.05)
Child's gender (boy=1)	0.4073	0.3147	0.4156
	(2.42)*	(1.06)	(2.07)*
First born (yes=1)	0.1339	0.1684	0.0046
	(0.69)	(0.46)	(0.02)
Child's age	0.3439	0.2679	0.3048
	(8.67)**	(4.55)**	(2.58)*
Distance to the nearest school[(a)]	-0.9786	-1.4678	-1.0661
	(2.53)*	(2.56)*	(2.60)**
Constant	-2.8717	5.1939	-6.4822
	(0.89)	(1.20)	(1.47)
H_0: $\beta_{informal} = \beta_{formal}$ (P-value)	0.1104	0.7624	0.0520+
Alpha (α)	1.3526	1.5237	1.1393
	(5.73)**	(2.13)*	(5.31)**
Wald χ^2 (all coefficients=0)	232.35	67.54	51.07
Prob > χ^2	0.0000	0.0000	0.0000
Observations	483	286	197

*Note: Robust z statistics in parentheses, + significant at 10%; * significant at 5%; ** significant at 1%; Model in column 2, the test of α=0 is accepted at the 5% level, either the Poisson or NB can be applied in this case. The estimated results by the NB and Poisson estimators are similar. All the models were controlled for location dummies.*

Chapter 8: Conclusions

8.1 Conclusions

This thesis has examined how the poor in peri-urban areas of Ho Chi Minh City (HCMC), Vietnam access credit and the impacts of that credit on education and healthcare spending, and child schooling.

Such examination is needed because as shown in the thesis, the role of education in earnings has become much more important during the transition to a market economy in Vietnam. The rate of return to schooling in Vietnam has increased quickly and has reached the global average rate of return of about 10%. The increase in the rate of return to schooling and the demand for skilled workers provides an exit from poverty for the poor in urban and peri-urban areas who rely heavily on labour income. But to use this exit they need to invest more in human capital, such as healthcare and education. One way for the poor to increase their investment in human capital is through microcredit, but the poor in peri-urban areas are highly credit-constrained and rely heavily on informal credit. There is distinction in borrowing behaviours between poor households in rural and urban wards in these peri-urban areas. In urban wards, the poor depend more on limited and subsidized funds from the government and are less likely to borrow from informal credit which provides loans based mainly on interpersonal trust rather than collateral. Households in rural areas who live further away from banks find it easier to borrow, while households in urban areas living near banks have a lower probability of borrowing and are more credit-constrained. There are two main possible reasons: the first is mutual help among people in rural areas where they have better interpersonal trust, while this trust is weak in urban areas; the second is complicated procedures such as lending procedures and property ownership certification blocking the poor from credit resources.[89] Apart from loans from government funds, the poor are almost always excluded from other formal credit resources.

Although the poor are highly credit-constrained, a sizable proportion of them have obtained credit, from either government subsidized or informal credit sources. This credit participation has positive and significant effects on household

[89] Kim (2004) provides a good example of the complicated procedure required by HCMC government to obtain certificates of land and house ownership.

education and healthcare spending. However, after disaggregating it appears that only formal credit has benefited the poor in terms of increasing education and healthcare spending because loans from informal credit sources, which are often very short-termed and small-sized, are not suitable for human capital investment. Allowing for heterogeous impacts also shows credit has larger impacts for households with initially low levels of healthacre spending. A gender disaggregation of impacts on education shows larger positive effects for girls.

Formal credit has brought beneficial effects to children's education (both expenditure and child schooling outcomes), whereas informal credit has failed to do so. Consequently, to improve child schooling in the long run requires easing access to formal credit for the poor; otherwise, the poor will rely upon informal credit and will end up in debt and may then pull their children out of school. As a result, informal credit may exacerbate poverty in the long term rather than help the poor out of poverty.

8.2 Avenue for future research

Future research should take into account some of the limitations in this thesis as indicated below.

First, one may think about possible endogeneity of education due to unobservable individual ability and the methods which fail to control for schooling quality that could lead to bias in the estimated returns to schooling. The fixed effect models with panel data would overcome the bias by estimating returns to changes in schooling over time (two points of time). Alternatively, future research using data on siblings' education or IQ index with an instrumental variable model can be feasible approaches; siblings' education may be highly feasible in the context of available data in Vietnam to overcome the endogeneity problem. Another approach, though it may be harder to find data for, is to use parents' education to predict wage-earner's education; this approach could be applied to younger groups of the sample, but for the older groups, their parents' education data would be unavailable in Vietnam.

Second, credit participation and constraints can also be determined by unobservable attributes, such as households' entrepreneurial ability, attitude to risks and access to social networks. In the current questionnaire used for collecting data for this thesis, I designed some questions (in Section 6 of the questionnaire attached) to capture the access to social networks, but the "yes/no" questions did not reflect fully the access to social networks. Future studies should design questions to represent levels of households' actual contribution or involvement in the social networks, and to measure entrepreneurial ability and attitude to risk, which will enable researchers to control for influences by these variables and confirm the current thesis findings.

Third, the PSM estimates are considerably lower than those of the OLS because PSM compares borrowers with similar non-borrowers, though still based on observable characteristics. Controlling for the pre-treatment income and assets, which are more likely to be associated with some main unobservable attributes such as motivation, entrepreneurial ability and skills, would reduce the bias. However, the pre-treatment variables may not capture all the unobserved bias, thus future research should develop some indicators to represent these attributes and control for the indicators when estimating propensity scores. For example, likert-scale questions such as indicators for parents' attitude to children's education, indicators for individual attitude to risk or entrepreneurial ability, or indicators representing a household's social network should be used to confirm and consolidate my findings.

Future research may also use the instrumental variable method to overcome the endogeneity problem. Distance to the bank is commonly used as IV in the literature, but it does not work in peri-urban areas because distance affects both credit participation and the outcomes (since banks and services are clustered together). Therefore, future research should look for appropriate IVs for peri-urban areas, for example, access to credit information could be a better IV than the distance to the nearest bank.

Fourth, the conclusion of heterogeneous impacts in Chapter 6 relied on the assumption that the sample population is homogeneous, hence 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 I assume it is unobservables rather than local treatment effects causing the heterogeneity, I do not necessarily need an instrumental variable estimator. However, the assumption that the selection into the treatment is based on observables, may not be true; in future research one should look for good instruments for peri-urban areas and the QTE with instrumental variables (IQTE) may be more precise than the conventional IV estimator at the median (Abadie, Angrist, & Imbens, 2002) and can address the potential bias.

Fifth, future studies also need to investigate impacts on child academic performance, higher education and other health indicators such as height for ages, BMI, malnutrition rate, etc. to confirm the effect findings.

Finally, the sample used in this thesis is likely to be representative of the poor group whose initial income per capita is below the poverty line at the survey time in this particular district but not necessarily for Ho Chi Minh City nor for Vietnam. In future if resources suffice, one should enlarge the sample size and cover of survey areas to some other peri-urban districts of HCMC, then the result will be representative of both the poor in HCMC and Vietnam as a whole because HCMC is the fastest urbanizing and biggest city in Vietnam.

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Project:

Household Credit Participation and the Impact on Education and Healthcare: Evidence from peri-urban areas of Ho Chi Minh City, Vietnam

RESEARCH INFORMATION SHEET FOR PARTICIPANTS

Dear Participants

Below is concise information about the researcher's project, please read carefully and do not hesitate to ask us for more information if you do not understand clearly.

1. Researcher's name and contact information

Thanh Tinh Doan, PhD Student
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Waikato Management School,
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The researcher is pursuing a PhD program at the University of Waikato, New Zealand. His research interests are development issues such as poverty, microcredit, education, health and household livelihood.

2. Research supervisor's name and contact information

Prof. John Gibson (chief supervisor)	**Prof. Mark Holmes** (second supervisor)
OP37, G.01 Orchard Park Department of Economics, Waikato Management School The University of Waikato Private Bag 3105, Hamilton, New Zealand Phone: +64-7-838.4289 Fax : +64-7-838 4358 Email : jkgibson@mngt.waikato.ac.nz Website: www.mngt.waikato.ac.nz	MSB.2.20 Department of Economics Waikato Management School, The University of Waikato Private Bag 3105, Hamilton, New Zealand Phone: +64-7-838.4454 Fax : +64-7-838 4358 Email: holmesmj@mngt.waikato.ac.nz Website: www.mngt.waikato.ac.nz

3. Brief objectives of this research

The research tries to investigate the microcredit market and its impact on household education and healthcare in suburban areas of Ho Chi Minh City, Vietnam. The research focuses not only on formal microcredit but also on informal microcredit transactions.

More specifically, in order to reach the targets the researcher tries to answer the following questions

- Who are customers of microcredit organizations? In other words, what are determinants of household credit participation and credit constraints?
- What are the impacts of credit participation on household health care, education expenditure, and on children's schooling?

4. Research participants

The participants of this research are households and household members in the selected areas. Participants/households are randomly selected from the district population of the poor; the researcher does not rely on any subjective criteria when he selects your household into the sample.

5. Tasks and expected time of the survey

We (field team) will interview you (as a household head or household head's spouse) and may have you complete some sections of the questionnaire. If you do not understand the questions or would like to ask for more information, you are encouraged to ask us. This interview may take about one hour.

6. Guarantee for confidentiality to information collected

The data and interview responses will be used by the researcher to write descriptive and econometric analyses of the research issues, which the researcher has chosen. Only the researcher and his supervisors Prof John Gibson and Prof Mark Holmes will be privy to the questionnaires, notes, data and the information collected.

Questionnaires and notes will be destroyed upon completion of data entry, and the researcher will keep a copy of the data on files but will treat it with the strictest confidentiality, data file will be locked in his office. No participants will be named in research reports unless an explicit consent has been given by the participants.

To assure the confidentiality for your household information, we will detach the coversheet and wipe off the "household number" on the coversheet after data entry, and store the coversheet with the consent form. When finishing data entry we will delete a column of household members' names, we only use members' IDs or codes to manage the observations in data files. Finally, we will destroy the questionnaire with your information on it.

In addition, at the beginning of each survey day the researcher and his supervisor will distribute 04 questionnaires to each interviewer (including 01 reserved questionnaire) and 04 envelops with the researcher's contact detail on them. The field team will put the questionnaire into envelops, and then paste and seal envelops after finishing interview. We will ask you to sign on the seals to make sure nobody can change information collected. At the end of the day, the researcher and his survey supervisor will gather all questionnaires completed including unused questionnaire and store at the researcher's home. On the next day, the task will be the same for other households, and the supervisor will go to your (interviewed) household to check whether the field team had done the interview. After checking, he will certify the questionnaire by signing on the questionnaire coversheet at the researcher's office (in Vietnam). After conforming to these strict steps, data entry will be entered into files and the questionnaires will be destroyed.

Only the researcher and his academic supervisors will be allowed to access to the information/data collected. The researcher will keep a copy of dataset on file but will treat it with the strictest confidentiality. The researcher will build a separate dictionary file to exploit the dataset, without it nobody can understand and use the dataset successfully. In addition, the researcher will set password for the dataset and dictionary file. Therefore, we hope that this procedure assures the confidentiality for the information that your household provides us.

7. You have the right at any time before, during and after the research period to:

- Before starting the interview, we would like to inform you that if you take part in the study, you have the rights to refuse answering any particular question, and to withdraw from the study at any time *before* completing the data collection, and

- You have the rights to ask any further questions about the study if you would like to have more information during the interview and after the survey, and
- You have the rights to access to a summary of the findings from the study when it is concluded by sending the researcher email, post mail or phone. The researcher will provide you the required information, which is related to the research.

Consent Form for Participants

THE UNIVERSITY OF WAIKATO
Te Whare Wānanga o Waikato

Project:

Household credit participation and the impact on education and healthcare:
Evidence from peri-urban areas of Ho Chi Minh City, Vietnam

CONSENT FORM FOR PARTICIPANTS

I have read the **Information Sheet for Participants** for this study and have had the details of the study explained to me. My questions about the study have been answered to my satisfaction, and I understand that I may ask further questions at any time.

I also understand that I am free to withdraw from the study at any time, or to decline to answer any particular questions in the study. I agree to provide information to the researchers under the conditions of confidentiality set out on the **Information Sheet**.

I agree to participate in this study under the conditions set out in the Information Sheet form for participants.

Signed: ______________________________

Name: ______________________________

Date: ______________________________

Researcher's Name and contact information:

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Confidential

File_HH

THE UNIVERSITY OF WAIKATO

Waikato Management School

Department of Economics

HOUSEHOLD QUESTIONNAIRE

March to May 2008 - Vietnam

Household number:…………………………………………………..

Household head (name):.. Sex | M | F

Number of people in the household:……………………………..

Address.................street.......................................ward........................ phone:………………….

Name of respondent:…………………………………… Code (in household roster):

Name of interviewer:……………………………………

Date of interview: day...…month...…...year 2008

	Degrees (ddd)	Minutes (mm.mmm)	Direction
GPS latitude			N
GPS longitude			E

Supervisor
(sign)

Interviewer
(sign & name)

Note: Supervisor will sign after visiting the households described on this sheet and confirming that they were interviewed on the day indicated, and all sections in this questionnaire were checked.

SECTION 1: HOUSEHOLD ROSTER (LIST OF HOUSEHOLD MEMBERS)

File_HM1

Code	1. You please tell us full name of each person who has been having meals, sleeping and sharing income and expenditure in your household, start with household head. Write down in capital letters and in order of satellite families	2. Sex Male.......1 Female...2	3. Relationship to head of household Head............................ 1 wife/husband................ 2 child.................................. 3 parents.............................. 4 sister/brother................. 5 grandfather/grandmother... 6 grandchild..................... 7 other relationship............ 8	4. How old is [name]? (if [name] is less than or equal 05, both month and year should be recorded) record 2 digits years	record 2 digits months	5. How is [NAME]'s residency status? Permanent=1 Semi-permanent (KT3) =2 Others =3	6. What is the current marital status of [NAME]? (only ask persons from 13 years old and over) Never married.............. 1 married........................ 2 widowed.................... 3 divorced..................... 4 separated.................... 5	7.Job of [name]? 1=farmer 2=small trader 3=street vendor 4=fac worker 5=professional 6=entreprenuer 7=retired 8=government 9=housework 10=jobless 11=other(specify)
	s1q1	**s1q2**	**s1q3**	**s1q4a**	**s1q4b**	**s1q5**	**s1q6**	**s1q7**
1								
2								
3								
4								
5								
6								
7								
8								
9								
10								
11								
12								
13								
14								
15								
16								
17								
18								
8. During the 12 months prior to the last 12 months, what was household's residency status in Q5? and household Head's status in Q6 and Q7? (record answer in the corresonding cells in the right hand side)						s1q8a:	s1q8b:	s1q8c:

SECTION 2A: EDUCATION (ask all members)

FILE_HM2

Code	**1.** Name (start with household head) (record exactly the same code of household member in the Roster)	**2** Can [name] reade & write? Yes=1 No=2	**3**. What is the highest education [NAME] obtained? 0=no garde completed 1-12 school years 13=technical w orker 14=vocational 15=college 16=bacherlor degree 18=master 20=doctor	**4** In the last 12 months has [NAME] attended school? (ask people below or equal 18) Yes=1 No..=2 (>>go to section 2B)	**5** What type of school has [name] studied in last 12 months 1=Public 2=semi-public 3=private	**6** In the last 12 months, What is the expenses for [NAME] to go to school (include pre-school/kindergarten expenses) try to ask and fill in the detail columns if no expenditure, record 0 if remember total amount & some detailed expenses, fill in corresponding columns thousands dong a tuition and registration fees to study outside of school	b contribution for school, class (building, parent association,...)	c Uniforms and other clothing required by the school?	d Textbook, reference book?	e Other school tools (paper pens, bag, pencils....)	f Extra classes (include language, computer)	g Other expenditure? (transport, accomodation others,...)	h Total (a+b+...+g)	**7** Expenses for other courses? (homework, tutorial, typewriting, foreign language computer skills, other studies? thousands dong
	s2aq1	**s2aq2**	**s2aq3**	**s2aq4**	**s2aq5**	**s2aq6a**	**s2aq6b**	**s2aq6c**	**s2aq6d**	**s2aq6e**	**s2aq6f**	**s2aq6g**	**s2aq6h**	**s2q7**
1														
2														
3														
4														
5														
6														
7														
8														
9														
10														
11														
12														
13														
14														
15														
												TOTAL		
												FILE_HH2	**s2aq6**	**s2aq7**

SECTION 3: HEALTH

FILE_HM3

FILE_HH3

Pls provide us some information on your household's health care

1. In the last 12 months, has any member of your household gone to the health care centre and/or hospital?
(including doctor's visit and cases whereas he/she is not sick or ill but taking health check, prenatal check-up, abortion, setting a coil, paid vacination….)

Yes ….. 1 (>>2)
No …… 2 (>>7)

s3q1

Code	**2** Name of person used health care services (record exactly the same code of household member in the Roster)	**3** Which health facility has [NAME] used? (including invited a health care provider to home) w ard health center... 1 district health center. 2 polyclinic.................. 3 government hospital. 4 private health facility. 5 traditional medical practitioner............... 6 7 other health facility... 8	**4**. Was [name] hospitalized then? Yes …..1 (>>6) No, just be an outpateint…2 (>>5)	**5.** What is the total out-patient treatment cost of [name]? (incl. consultation and other expenses like feeding-up allow ance, other service fees as requested medicine, health tools ..) related to treatment for one time Unit: 1000 VND >> TIMES & NEXT PERSON			**6.** What is the total in-patient treament cost of [name] (incl hospital fee and other expenses like feeding-up allow ance, other services as requested medicince, health tools…) related to treatment for one time Unit: 1000 VND >> TIMES & NEXT PERSON		
				amount/once	times	amount	amount/once	Times	Amount
	s3q2	**s3q3**	**s3q4**	**s3q5a**	**s3q5b**	**s3q5c**	**s3q6a**	**s3q6b**	**s3q6c**
1									
2									
3									
4									
5									
6									
7									
8									
9									
10									
11									
12									
13									
14									
15									
16									
17									
18									
19									
20									
21									
					TOTAL	**s3q5**			**s3q6**

s3q7. In the last 12 months, how much did your household spend on buying medicine for self treatment or stand-by without consultation
(incl. medicine & other expenses such as: transportation, vehicle parking fee ...)

s3q8. In the past 12 months, how much has your household spent on health tools? Example: stethoscope, hearing aid apparatus, taking machine, sphygmomanometer, medicine cabinet…

s3q9. In the past 12 months, how much has yr household contributed to social health (health fund, construction of health centres, preventive compaigns, …)

s3q10. How much has your household paid for health insurance in the past 12 months?

s3q5. Total of s3q5c (out-patient)

s3q6. Total of s3q6c (in-patient)

s3q11. Total Household's health expenditure
(=s3q5+s3q6+s3q7+s3q8+s3q9+s3q10)

SECTION 4: HOUSEHOLD CREDIT

FILE_HH6

1. In the last 12 months, do you or your household have an account (borrowing or saving, or ATM at any bank or other financial institutions)?

yes..........................	1	**s4q1**
No...........................	0	

2. In the last 12 months, have any household members demanded to borrow? (incl the demand was satisfied and not satisfied)

yes………………..	1 (>>3)	**s4q2**
No...........................	0 (>>4)	

3. Was the demand satisfied?

Yes, full…….1	**s4q3**
Yes, partly…2	
No…………..0	

4. Have you or your household members borrowed (in cash or in kind) in the last 24 months from relatives, friends, banks, social-politial organizations credit fund, rotating credit and savings association, pawnbrokers…. ?

yes............. 1(>> 5)	**s4q4**
No............. 0 (>>go to Section 5)	

5. Have you or your household members borrowed (in cash or in kind) in the

yes.............1	**s4q5**
No...............0	

Order	6. What are the sources of your loans in last 24 months Social Policy Bank……………………..1 Bank for agriculture and rural Other commercial banks………………3 Job placement support fund………….4 Credit Cooperatives……………………5 People Credit Fund……………………..6 Socio-polical organizations……………7 Private moneylenders………………….8 Relative, friends………………………..9 Rotating Credit&Saving Associations..10 Hunger elimi & povt reduction fund…..11 Pawnbrokers…………………………..12 Others………………………………….13	7. What is the value of your household's loan?	8. When did your household borrow the loan? (only for last 24 month loans)		9. What is the loan's purpose? Consumption................1 Debt repayment………..2 House purchase/ building/maintenance....3 Land purchase………..4 Wedding/funeral/ woship/birthday party….5 Study fee……………. ..6 Health care……………..7 Production/business......8 Others (specify)..........9	10. What is the interest rate of this loan? (if the interest rate is not specified, record Time Unit and/or Interest Amount)			11.Did your household use assets as collateral for this loan? Yes=1 No= 0	12. What is this loan contract terms (record as in credit contract)	
		Thousand VND	Month	Year		Rate (%)	Time unit	Interest amount		years	months
	s4q6	**s4q7**	**s4q8a**	**s4q8b**	**s4q9**	**s4q10a**	**s4q10b**	**s4q10c**	**s4q11**	**s4q12a**	**s4q12b**
1											
2											
3											
4											
5											
6											
7											
8											
9											
TOTAL											

SECTION 5A: FOOD CONSUMPTION AND DRINKS								FILE_HH5A
1. Within the past **7 days**, did the members of your household eat/drink any [. . .] within the household? PLEASE ONLY LIST ITEMS CONSUMED WITHIN THE HOUSEHOLD AND EXCLUDE FOOD CONSUMED OUTSIDE THE HOUSEHOLD WHICH SHOULD BE INCLUDED IN No 10 ASK FOR ITEMS BEFORE MOVING TO Q2.			2. Within the past 7 days did anyone in your household **purchase** any […]?	3. Within the past 7 days did anyone in your household consume any […] from a **stock** you keep?	4. Within the past 7 days did anyone in your household consume any […] from **gifts/assistance** you received or any other sources?	5. Within the past 7 days did anyone in your household consume any […] from **your own production**?	6. REVIEW QUESTIONS 2-5. IS AT LEAST ONE ANSWER 'YES'?	7. How much would it have cost your household to purchase the same amount?
		YES..1 NO…0 (»NEXT)	YES..1 NO…0	YES..1 NO…0	YES..1 NO…0	YES..1 NO…0	YES..1 NO…0	,000 VND
		s5aq1	**s5aq2**	**s5aq3**	**s5aq4**	**s5aq5**	**s5aq6**	**s5aq7**
1	Cereals and Cereal products							
2	Noodles/rice noodle							
3	Meat, meat products, fish							
4	Vegetables							
5	Fruits							
6	Cooking mixed spices							
7	Sugars, milk and milk products							
8	Beverages/alcohol/beer..							
9	Coffee, tea, cigarettes							
10	Outdoor eating/party							
							TOTAL Q7	
8. Total Food consumption and drinks for last 12 months (Total Q7 x 52 weeks)							**s5aq8**	
9. Compare with period of 12 months prior to the last 12 months, how much (%) did the Total Q7 change?							**s5aq9**	

SECTION 5B: NON-FOOD EXPENDITURES (DAILY) — FILE_HH5B

Code	1 In the las 12 month, which of the following items did your household consume/purchase? mark X if the answer is yes ask Q1 for all items before starting Question 2	X	2 How many months did your househlod buy this item in the last 12 months ?	3 How much did your household buy this item each month? ,000 VND
	Item	s5bq1	s5bq2	s5bq3
100	Pocket money for children?			
101	Coal, wood, sawdust, chaff?			
102	Gas?			
103	Kerosene for cooking or light?			
104	Gasoline, lubricant and grease for motor, car…			
105	Bicycle, motorcycle or car parking fee?			
106	Matches, candles, flint?			
107	Washing powder			
108	Softening liquid ?			
109	Disk washing liquid,			
110	House cleaning liquid?			
111	Shampoo, conditioning?			
112	Bath soap, liquid			
113	Lotion, powder & lipsticks			
114	Toothpaste, tooth brush?			
115	Toilet paper, razorblades,			
116	Books, newspapers, magazines?			
117	Flowers?			
118	Entertainment? (cinema, video, sports)			
119	Lottery tickets?			
120	Regular worship items?			
121	Haircut, hairdressing?			
122	Other daily expenses			
			Total s5bq3	

4. Compare with a month in the period of 12 months prior to the last 12 months, how much (%) did the Total of q3 change on average? **s5bq4** %

SECTION 5C: NON-FOOD EXPENDITURES (ANNUALLY) — FILE_HH5C

CODE	1. In the last 12 month, which of the following items did your household consume/purchase? mark X if the answer is yes; ask question 1 for all items before q2	X	2. Value of purchase in the last 12 months? ,000 VND
	Item	**s5cq1**	**s5cq2**
123	Fabric?		
124	Ready-made clothing (incl. Underwear)?		
125	Mosquito net and netting?		
126	Face towel, scarves?		
127	Rush mats, blankets, pillows?		
128	Other sewing materials and garments? (needles, thread, socks...)		
129	Tailoring or laundry service?		
130	Shoes, sandals, wooden clogs?		
131	Nylon sheeting, hats, umbrellas?		
132	Light bulbs, electric wire, plugs, fuse?		
133	Porcelain and glass bowls, plates, teapots and cups,…		
134	Pans, pots, bins, buckets, basins?		
135	Vacuum thermos and liner?		
136	Bags and baskets?		
137	Lighter, flashlight, battery...?		
138	Cradle, hammock, pram?		
139	Other household items? (EXCL durable goods)		
140	Bike tires, tubes, bicycle spare parts?		
141	Motorbike, car tires, tubes, motorcycle, car spare parts?		
142	Maintenance and repair of living tools		
143	Boat, bus, train, taxi, car, transportation fees?		
144	Pictures, photos, houseplants?		
145	Sport instruments		
146	Toys (for children and common)?		
147	Envelopes, stamps, telephone, postage fees?		
148	Internet charges		
149	Cosmetic surgery, body building?		
150	Excursion, holidays?		
151	Jewelry, watch, makeup?		
152	Other cultural activities?		
153	Hiring domestic services?		
154	Other annual expenses		
		Subtotal (s5cq2a)	
155	Contributions to social funds (for natural relief, poverty reduction fund, education encouragement fund…)		
156	Public labor contribution		
157	All kinds of taxes (excl. production tax)		
158	Wedding, birthday, one-month/one-year old baby party…		
159	Funeral and worship on special occasions in your household		
160	Arranged parties in your household		
161	Give, donation, support, assistance,..		
162	Other expenses		
		Subtotal (s5cq2b)	
		Total s5cq2	

3. Compare with period of 12 months prior to the last 12 months, how much (%) did the Total q2 change? **s5cq3**

SECTION 6: Services and information access

FILE_HH6

Pls provide us some information about local insfractructure, access to social services and market, and information

1. Are there any phones in your household including cellphone? **s6q1** Yes…1 No….0

2. Does your household use internet? **s6q2** Yes…1 No….0

3. Are there any TVs in your household? **s6q3** Yes…1 No….0

4. Are there any radio in your household? **s6q4** Yes…1 No….0

5. Does your household subcribe newspapers/magazines? **s6q5** Yes…1 No….0

6. Has any household member participated social organizations (women, youth, farmer, veteran union…)? **s6q6** Yes…1 No….0

7. Pls tell us name of the nearest [……] to your household (including other ward and/or other district)

s6q7	Institutions	Name and address	Metre
	Government and market		
a	Daily market		
b	Trade center and supermarket		
c	District People's Committee		
d	Ward People's Committee		
	Financial institutions		
e	Bank		
f	Other credit/financial institution		
	Schools		
g	Pre-school/kindergarten		
h	Primary school		
k	Lower secondary school		
l	Upper secondary school		
	Health facilities		
m	Health center		
n	Hospital		
o	Medical diagnostic clinic		

SECTION 7: HOUSING **FILE_HH7**

Pls provide us some information about your housing.

1. How many houses/flats does your family own? s7q1 [ ]

2. How long has your household been living in years s7q2 [ ]

3. Does this house/flat belong to you? s7q3 [ ]
   yes, totally 1
   yes, partly......... 2
   No.................... 3

4. Do you have to pay for house rent s7q4 [ ]
   yes................... 1
   no.................... 0(>>6)

5. How much did you pay for rent of your dwelling in the last 12 months (in cash and in kind)? [ ]
thousand VND **s7q5**

6. What is the current price of your dwelling ? s7q6
thousand VND [ ]

7. Apart from this dwelling, do you have any other landlot or house/flat? [ ]
   Yes.................. 1
   No…................. 0(>>12) s7q7

8. What is the current price of this landlot or house/flat? s7q8
thousand VND [ ]

9. Did you buy any land or house/flat in the last 12 months? s7q9 [ ]
   yes.................. 1 (>>11)
   no..................... 0 (>>10)

10. When was the last time of purchase? month [ ] year [ ]
if you bought before the last 12 months (>> 13) s7q10a s7q10b

11. How much did you pay for in the last 12 months ?
thousand VND [ ] **s7q11**

12. Do you have any newly built house/flat compled in the last 12 months? [ ]
   yes................... 1
   no..................... 0(>>14) s7q12

13. How much did you spend on construction from starting to completion? thousand VND [ ] s7q13

14. How much did you spend on big repairation, renovation, improvement of your house/land in the last 12 months? thousand VND **s7q14** [ ]

15. How much did you spend on small repair in the last 12 months (incl. painting ..) thousand VND [ ] **s7q15**

16. Do you have to pay for living & drinking water? s7q16 [ ]
   yes............ 1
   no.............. 0 (>>18)

17. How much did you have to pay for this water in the last 12 months? (01 month bill x 12 months) [ ]
thousand VND **s7q17**

18. Did you have to pay for living electricity in the last 12 months [ ]
   yes............ 1
   no.............. 0 (>>20) s7q18

19. How much did you pay for electricity used for living purpose the last 12 months? (01 month bill x 12 months) thousand VND [ ] **s7q19**

20. Do you have to pay for garbage disposal? [ ]
   yes............ 1
   no.............. 0 (>>22) s7q20

21. How much did you pay for living garbage disposal ? (01 month bill x 12 months) thousand VND [ ] **s7q21**

22. Sum of expenses on housing, electricity, water, and garbage disposal (5+11+14+15+17+19+21) thousand VND [ ] **s7q22**

SECTION 8: FIXED ASSETS AND OTHER DURABLE ASSETS

1. Pls let us know what kind of following things does your household have (ask household head or his/her spouse)?

Code	Assets, tools	mark x if yes
101	Perennial crops garden	
102	Aquaculture production area	
103	Other agricultural land area	
104	Buffalo, cow for production and breeding	
105	Breeding male and female pig	
106	Basic poultry, cattle	
107	Breeding facilities of farming	
108	Workshop	
109	Shop	
110	Other production base	
111	Car	
112	Truck	
113	Pulling machine	
114	Trailer	
115	Motorbike	
116	Bicycle	
117	wagon	
118	Moteur boat, boat	
119	Other means of transportation	
120	Lathe, welding, cutting machine	
121	Casting machine	
122	Wooden sawing machine	
123	Pumping machine	
124	Power generator	
125	Printer, photocopy machine	
126	Fax machine	
127	Telephone (desk/mobile)	
128	Sewing, weaving, embroider …	
129	Other machine and equipment	

Code	Assets, tools	mark x if yes
130	fishing net	
131	Goods keeping things	
132	Other professional equipment	
133	Video	
134	Color T.V.	
135	Black white T.V	
136	Applifier/speakers	
137	Radio / Cassettes	
138	Recorder	
139	Computer	
140	Camera, CD, VCD, DVD players	
141	Refreezerator, Freezer	
142	Air-condioner	
143	Washing, drying machine	
144	Electric fan	
145	Water heating machine in the bathroom	
146	Gas cook	
147	Electric cook, rice pan, airpressure pan	
148	troller (various kinds)	
149	Wardrobe (various kinds)	
150	Bed	
151	chair, table, sofa, ...	
152	vacuum cleaner, exsisccate	
153	Antique, piano, oocgan, dressing table	
154	Other valuable things	
155		
156		
157		
158		

SECTION 8: FIXED ASSETS AND OTHER DURABLE ASSETS (CONT)

FILE_HH8

Row No	2 Name of assets, other durable assets (MARKED X previously)		3 How long did your household buy/receive this item? and how much does this item value at the present? (Unit: 1000 VNĐ)			
			less than 24 months		more than 24 months	
	s8q2	Code	Yes	Value	Yes	Value
1						
2						
3						
4						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22						
23						
24						
25						
26						
27						
28						
29						
30						
	TOTAL		s8q3a		s8q3b	

HOUSEHOLD CREDIT SURVEY

FILE_HH9

SECTION 9: COMMUNITY/WARD CHARACTERISTICS (ask ward-government officers)

Ward:……………………………… Code:……..

Pls provide us some information about local insfractructure and social services

1. How many primary schools are there in this ward?		**s9q1**
2. How many lower secondary schools are there in this ward?		**s9q2**
3. How many upper secondary schools are there in this ward?		**s9q3**
4. How many pre-schools/kindergartens are there in this ward?		**s9q4**
5. How many clinic, health center, hospital are there in this ward?		**s9q5**
6. How many financial/credit institutions are there in this ward excluding relatives and friends?		**s9q6**
7. How many commercial centers and supermarkets are there in this ward?		**s9q7**
8. How many daily markets are there in this ward?		**s9q8**

9. Pls tell us some information about education, healthcare and financial services in this ward or neighouring wards/districts which people in this ward often use. If the selected service is in this ward, tick "X" on "This ward".

	This ward	Name & address		Degree (ddd)	Minutes (mm.mmm)	Direction
Daily market 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Daily market 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Daily market 3			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Daily market 4			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Supermarket/commercial center 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Supermarket/commercial center 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
District People's Committee			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Ward People's Committee			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Bank 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Bank 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Bank 3			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Credit Institute 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Credit Institute 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Credit Institute 3			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Pre-school /kindergarten 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Pre-school /kindergarten 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Pre-school /kindergarten 3			GPS Latitude		.	**N**
			GPS Longitude		.	**E**

Question 9 (continue)

Primary school 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Primary school 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Primary school 3			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Lower secondary school 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Lower secondary school 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Lower secondary school 3			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Upper secondary school 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Upper secondary school 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Health center 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Health center 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Hospital 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Hospital 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Medical diagnostic clinic 1			GPS Latitude		.	**N**
			GPS Longitude		.	**E**
Medical diagnostic clinic 2			GPS Latitude		.	**N**
			GPS Longitude		.	**E**