Migration, Richesse et Consommation des Ménages en Chine Rurale

Mengbing Zhu

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Mademoiselle Mengbing ZHU

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Devant le jury composé de :

Mme Sylvie DÉMURGER, Directrice de recherche CNRS, GATE – Directrice de thèse
M. Shi LI, Professeur, Beijing Normal University – Tuteur de thèse
Mme Carine MILCENT - Chargée de recherche CNRS, HDR, PSE et CEFC – Examinatrice
M. Qingjie XIA, Professeur, Peking University – Rapporteur
M. Ximing YUE, Professeur, Renmin University of China – Examinateur
Mme Lei ZHANG, Associate Professeur, Shanghai Jiao Tong University – Rapporteure

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ABSTRACT

As a large agricultural country, rural issues become more and more serious in the modernization process of China. The income gap, income inequality and its influencing factors have attracted much attention for a long time since income data is more accessible and intuitive, while systematic evidence is missing on consumption patterns and its influencing factors in rural areas. Arguably, income is difficult to be accurately measured and more likely to be affected by temporary shocks. Thus, consumption is an ideal measurement for predicting long-run economic well-being. Based on micro-household survey in rural China, this dissertation focus on how consumption in China is affected. No doubt that many factors may affect household consumption, and we pay special attention in this dissertation to the impact of migration and household wealth, for we consider these two issues are closely related to the tremendous changes in rural China. Meanwhile, another related issue, consumption poverty, is also discussed, especially the role that China's Rural Minimum Living Standard Guarantee Program plays in alleviation consumption poverty. This dissertation mainly consists of three parts, each of which is covered by one of three main chapters of the thesis.

In Chapter 2, given the mechanism that migration and remittances will affect educational decision and investment in rural China, we estimate their effects. Using rural household data from the China Household Income Project 2013, we employ the different methodologies to investigate the impact of migration and remittances on school enrollment and educational investment, such as the basic OLS and Tobit method. Meanwhile, to solve the endogeneity problem of migration decision and the receipt to remit, we also use instrumental variables. The result demonstrates that they both play a negative role. First, both migration and remittance decision adversely affect educational decision, especially for children in the older

age group. Second, we provide evidence of negative and statistically significant associations between migration-sending households/remittance-receiving households and educational investment. Furthermore, in households with one child at school, households without migrants or remittances care more about the quality of compulsory education. Two reasons can be given to interpret the lower investment in education in households with migrants or remittances. One is that the decision to migrate in poorer households is always simultaneous with the decision to remit, for explicit purpose, such as health care. The other possibility is the lower quality and returns to education in rural China, then households may view educational investment as a consumption good.

As we are well aware of the Life Cycle theory, as well as the Wealth Effect theory, Chapter 3 assesses the strength of the correlation between household wealth and consumption in China. Based on household survey data in 2002 and 2013, we find evidence of a positive and significant effect of wealth on consumption, and it increases over time for both urban and rural households. Estimates show that a one-yuan increase in household net wealth increases annual consumption in the range of 0.2 yuan in the short run in 2013. We also find that the wealth effect is much stronger in rural areas in both 2002 and 2013 since current income might be more important in the determination of household consumption in urban areas.

As the two main components of household wealth, financial and housing wealth are different in terms of liquidity, measurability and capital gain. Therefore, their effects on consumption may also be diversity. Since housing is the most important component of household wealth, it is not surprising that the effect of home value on household consumption is stronger than that of financial wealth. Moreover, the consumption elasticity of wealth also varies among households in different age groups and increases with income and wealth quintile.

In Chapter 4, we switch our angle to another related issue, consumption poverty and the performance of an anti-poverty policy, China's Rural Minimum Living Standard Guarantee Program. In addition to studying its influencing factors, consumption is also an important measurement to measure the incidence of poverty. To achieve the goal of completely eliminating poverty by 2020, the Chinese government launched the Precise Poverty Alleviation Program. As one of the most important strategy, China's Rural minimum living standard guarantee program (Dibao Program) aims to provide cash transfers to all households with incomes below the Dibao lines set at the county level. So in practice, the rural Dibao program should not only well target all the eligible households, but also have well-functioning checks and balances, to achieve a better perfect Dibao targeting. In this paper, based on rural household survey data in the year 2013, we evaluate the targeting performance of the rural Dibao program. The result reveals quite large targeting errors using traditional income identification criteria. However, taking education, health, housing and consumption dimensions into account, we propose a new selection criterion, the multi-dimensional identification criterion, to evaluate the targeting effectiveness of the rural Dibao program. Not surprisingly, the targeting effectiveness increases, but the coverage rate remains low.

Based on the empirical evidence from the chapters above, we put forward the following suggestions related to policy choice: First of all, we provide evidence that both migration and remittance decisions adversely affect educational investment. It is worth noting that policy makers should take some action to improve the educational investment in rural areas, especially for poorer households. And education officials should hire more qualified teachers to improve the quality of education in rural China. Secondly, we should be aware of the positive effect of wealth on consumption, as well as the unequal increasing distribution of household wealth in rural areas. Therefore, in order to simulate consumption as well as reduce consumption inequality, we should promptly promote the reform of property distribution, especially for those "non-property farmers". Third, the rural Dibao program can help to lift low-income households out of poverty, which depend highly on the targeting performance of this program. According to the bias between policy design and practice, we suggest to set a uniform range of standards for the rural Dibao program for local government to carry out, on the basis of the concept of Multidimensional Poverty Index. In addition, local governments should increase the amount of funding for the rural Dibao program and expand its coverage, especially in poor areas. Therefore, it is necessary to increase Dibao funding and expand its coverage, so it can further help to reduce consumption inequality.

Keywords: Migration; Remittances; Wealth Effect; Consumption; Cash Transfer; Rural poverty; Educational Investment

RESUME

En tant que grand pays agricole, les questions rurales deviennent de plus en plus importantes dans le processus de modernisation de la Chine. Les inégalités de revenus et leurs déterminants ont attiré l'attention des chercheurs depuis de nombreuses années car les données sur le revenu sont accessibles relativement aisément et intuitives. Par contraste, les modèles de consommation et leurs déterminants dans les zones rurales restent aujourd'hui encore peu étudiés. Or, la consommation est une mesure idéale pour prédire le bien-être économique à long terme alors que le revenu est difficile à mesurer avec précision et plus susceptible d'être affecté par des chocs temporaires. Sur la base d'une enquête microéconomique auprès de ménages en Chine rurale, cette thèse a pour ambition d'examiner les facteurs qui influencent et peuvent modifier les comportements de consommation en Chine rurale. Si de nombreux facteurs peuvent influencer la consommation des ménages, nous accordons dans cette thèse une attention particulière à l'impact de la migration et à celui de la richesse des ménages sur leur comportement de consommation car ces deux dimensions sont étroitement liées aux changements récents en Chine rurale. En complément, une question connexe, la pauvreté de consommation, est discutée notamment à travers le rôle que le Programme de Garantie Minimum de Standard de Vie en Chine rurale joue pour atténuer la pauvreté de consommation. Cette thèse se compose de trois chapitres qui reprennent séparément ces trois questions.

Dans le Chapitre 2, nous examinons empiriquement les mécanismes selon lesquels la migration et les transferts monétaires peuvent affecter les décisions d'éducation et d'investissement en éducation dans la Chine rurale. À l'aide de données sur les ménages ruraux extraites de l'enquête China Household Income Project (CHIP) 2013, nous employons

différentes méthodologies pour étudier l'impact de la migration et des transferts monétaires sur les niveaux de scolarisation et sur les investissements éducatifs. Dans ce type d'analyse empirique la question de l'endogénéité de la décision de migration et des transferts monétaires se pose, problème que nous traitons à l'aide de variables instrumentales. L'analyse empirique menée dans ce chapitre montre que la migration comme les transferts de fonds jouent un rôle négatif. Tout d'abord, la décision de migration et l'envoi de transferts monétaires affectent négativement la décision éducative, en particulier pour les enfants dans le groupe plus âgé. Deuxièmement, nous établissons une corrélation négative statistiquement significative entre les ménages de migrants / les ménages recevant des transferts et les investissements éducatifs. De plus, chez les ménages ayant un enfant à l'école, les ménages sans migrants ou sans transferts s'occupent plus de la qualité de l'enseignement obligatoire. Deux raisons permettent d'expliquer un investissement plus faible dans l'éducation dans les ménages ayant des migrants ou recevant des transferts. L'une est que la décision de migrer dans les ménages les plus pauvres est toujours simultanée à la décision d'envoyer des transferts monétaires, à des fins explicites, comme les soins de santé. L'autre possibilité est la qualité et le rendement inférieurs de l'éducation reçue en Chine rurale, ce qui peut conduire les ménages à considérer l'investissement éducatif comme un bien de consommation, et non un investissement.

Partant de la théorie du cycle de vie, ainsi que de la théorie de l'effet de richesse, le Chapitre 3 évalue la robustesse de la corrélation entre la richesse et la consommation des ménages en Chine. Sur la base des données des enquêtes ménages CHIP en 2002 et 2013, nous mettons en évidence un effet positif et significatif de la richesse sur la consommation, et qui augmente avec le temps pour les ménages urbains et ruraux. Les estimations montrent qu'une augmentation d'un yuan dans la richesse nette des ménages augmente la consommation annuelle de 0.2 yuan à court terme en 2013. Nous établissons également que l'effet de richesse est beaucoup plus fort dans les zones rurales en 2002 et 2013, car le revenu courant semble être plus important dans la détermination de la consommation des ménages dans les zones urbaines. Étant donné que les deux principales composantes de la richesse des ménages, la richesse financière et le patrimoine immobilier, sont différentes en termes de liquidité, de mesurabilité et de gain en capital, leurs effets sur la consommation peuvent aussi varier. Du fait que le logement est la composante la plus importante de la richesse des ménages, il n'est pas surprenant que l'effet de la valeur résidentielle sur la consommation des ménages soit plus forte que celui de la richesse financière. En outre, l'élasticité de la consommation de la richesse varie également en fonction des ménages dans les différents groupes d'âge et augmente avec le revenu et le quintile de richesse.

Dans le Chapitre 4, nous mettons l'accent sur une question connexe, la pauvreté de consommation et la performance d'une politique de lutte contre la pauvreté, le Programme de Garantie Minimum de Standard de Vie en Chine rurale. En plus d'étudier ses déterminants, la consommation est également un indicateur important pour mesurer l'incidence de la pauvreté. Pour atteindre l'objectif d'éliminer complètement la pauvreté en 2020, le gouvernement chinois a lancé une stratégie ciblée d'atténuation de la pauvreté. Au sein de cette stratégie, le Programme de Garantie Minimum de Standard de Vie (Dibao) vise à fournir des transferts en monétaires à tous les ménages dont les revenus sont inférieurs aux seuils Dibao établies au niveau des bourgs et de villages. En théorie, le programme Dibao rural devrait non seulement cibler tous les ménages éligibles, mais recourir également à des contrôles et ajustements systématiques afin de parvenir à un meilleur effet du ciblage de la politique. Dans ce chapitre, nous évaluons la performance de ciblage du programme Dibao rural à partir des données sur les ménages ruraux extraites de la base CHIP 2013. À l'aide des critères traditionnels d'identification des revenus, notre analyse révèle des erreurs de ciblage assez importantes. Cependant, en tenant compte de dimensions complémentaires liées à l'éducation, la santé, le logement et la consommation, nous proposons un nouveau critère de sélection, à savoir le critère d'identification multidimensionnelle, afin d'évaluer l'efficacité du ciblage du programme. Selon ce nouveau critère multidimensionnel, l'efficacité du ciblage augmente sans surprise, mais le taux de couverture reste faible.

Partant des résultats empiriques mis en lumière dans les trois chapitres de cette thèse, nous proposons les suggestions suivantes quant au choix des politiques publiques. Tout d'abord, nous mettons en évidence que les décisions relatives à la migration et aux transferts monétaires s'accompagnent d'un investissement négatif dans l'éducation en zone rurale. Ce résultat important souligne la nécessité et l'importance de prendre des mesures pour améliorer l'investissement dans l'éducation dans les zones rurales, en particulier pour les ménages les plus pauvres. L'un des canaux pourrait être d'augmenter le nombre d'enseignants qualifiés en Chine rurale pour améliorer la qualité et le rendement de l'éducation. Deuxièmement, les résultats empiriques du chapitre 3 ont mis en évidence l'effet positif de la richesse sur la consommation, ainsi que la distribution inégale croissante de la richesse des ménages dans les zones rurales. Par conséquent, afin de stimuler la consommation et réduire l'inégalité de la consommation, il serait important de promouvoir rapidement la réforme de la distribution des avoirs, en particulier pour les résidents ruraux n'ayant pas de terre. Troisièmement, le programme de dibao rural peut aider à éloigner les ménages à faible revenu de la pauvreté, ce qui dépend fortement de la performance de ciblage de ce programme. Compte tenu de l'écart entre la conception et la pratique des politiques, nous proposons de définir au niveau local un critère multidimensionnel pour le programme Dibao rural, sur la base de la notion d'Indice de Pauvreté Multidimensionnelle.

Nos résultats soulignent également la nécessité d'augmenter le montant du financement du programme Dibao rural et d'élargir sa couverture, en particulier dans les zones pauvres, ce afin de réduire les inégalités de consommation.

Mots-clés : Migration ; Transferts ; Effet de richesse ; Consommation ; Transferts monétaires ; Pauvreté rurale ; Investissement en éducation.

1. General Introduction

1.1. Study on household consumption in rural China

With the rapid development of economy, and as a large agricultural country, rural issues become more and more serious in the modernization process of China. By the year 2015, there were 0.6 billion rural residents in China, accounting for 43.8% of the total population (NBS,2016). Associated with a large number of surplus labor force, lower levels of educational attainment, as well as a lack of community resources in rural areas, the inequality between urban and rural China has increased substantially over time. Many studies on inequality mostly focus on the evolution of income or earning inequality in China (Meng 2004; Ravallion and Chen, 2007). Income disparities between urban and rural areas have been increasing remarkably in recent years, as shown in Figure 1. The urban-to-rural income ratio increased from 2.5 to 3.1 between 1996 to 2013. Nowadays, based on micro-level dataset, most of the existing literature studies income gap, income inequality and its influencing factors (Luo, 2012; Wang, 2005, etc.), Arguably, the "income" variable may not be an accurate measurement to reflect resources which are available to the households in the long run. In particular, for rural households, because of the complex and diverse sources of income[1], income is difficult to be accurately kept tracked. In addition, household income in rural areas is more likely to be

[1] It should be noted that household income in rural areas includes income from farming, nonagricultural sector, wage employment, property income and transfer income, in cash and in kind. Measurement errors could arise from the differences in the ability and the willingness of respondents to report accurate household income.

affected by any disaster or temporary shocks (Cutler and Katz, 1992). In companion, consumption is more precise and direct to measure welfare in the long term. Yet there is no systematic analysis of consumption patterns and its influencing factors in rural China. Studying consumption for rural households could not only help forecasting future consumption trends, but also help improving the potential demand for consumption, which can then drive economic development. Therefore, a systematic study on consumption status, consumption patterns and its influencing factors in rural areas should be conducted.

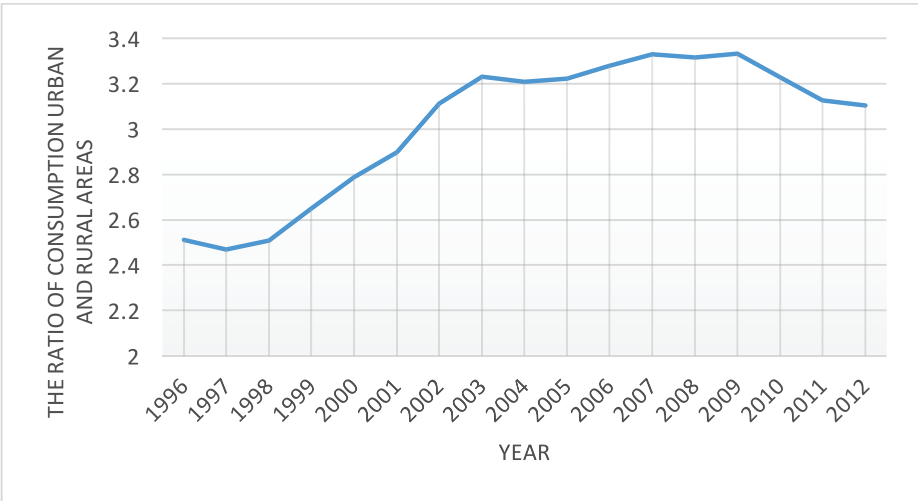

Figure 1.1 The ratio of consumption between rural and urban areas: 1996~2012

Source： China Statistical Yearbook

Consistent with the rapid economic development, both income and consumption in rural areas have sharply increased. Figure 1.2 displays the per capita income and consumption for rural residents from 1996 to 2012. It first shows that there is a significant positive correlation between income and consumption. Income per capita reached 7,917 yuan in 2012, which was 4.11 times higher than in 1996. During this period, per capita consumption increased from 1,572 yuan to 5,908 yuan, with an annual growth rate of 12.79 percent.

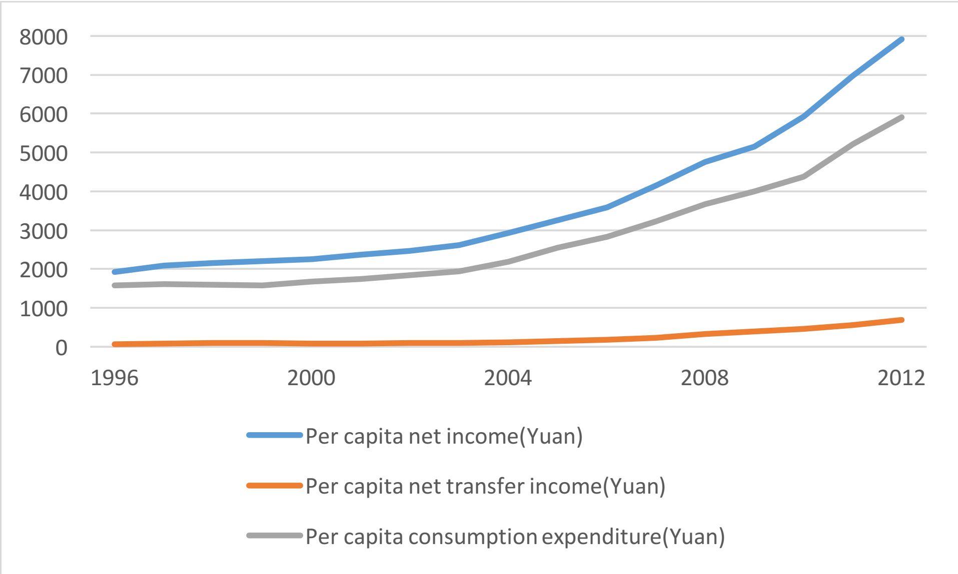

Figure 1.2 Per capita income and consumption for rural residents:1996~2012

Source: China Statistical Yearbook

Meanwhile, Figure 1.3 further shows the consumption components and their changes from 2000 to 2012. At a starting point, the Engel coefficient for rural residents decreased over this period, showing that expenditure on food accounted for less than 50% of total consumption in 2013. By contrast, consumption on housing, education and health care has been increasing. It is clear that nowadays rural residents spend more and more on investment goods rather than on consumption, which implies that the consumption profile of rural households is becoming more and more rationalized.

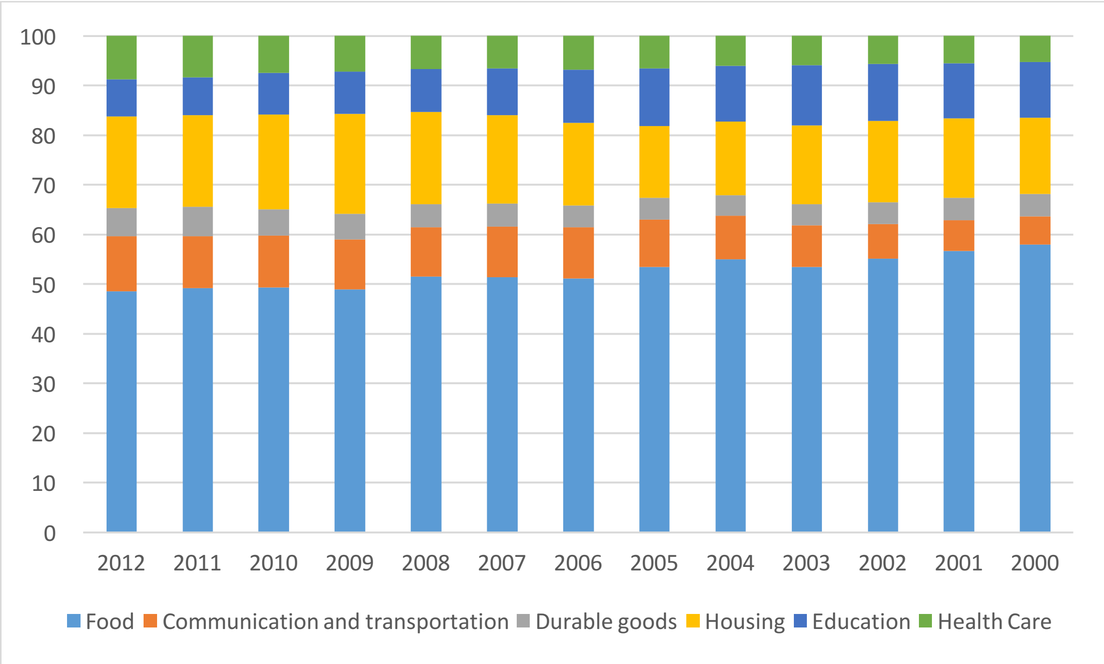

Figure 1.3 Budget shares for consumption expenses from 2000 to 2012

Source： China Statistical Yearbook

Understanding consumption and consumption patterns is crucial to measuring changes in living standards, as well as providing policy prescriptions to improve well-beings in rural China. There is no doubt that many factors may affect consumption at the same time. Based on the specific characteristic of rural areas, a central focus of my dissertation analyze two of them. One is the most important change in the labor market, i.e., the loosening of administrative controls over population movements between urban and rural areas and the increasing number of rural to urban migration. The other is the unprecedented changes in the accumulation of household wealth. In other words, at a starting point, I attempt to estimate how migration and household wealth affect consumption and consumption patterns.

1.2. The Great Migration and Educational Investment in China

1.2.1. Research related to migration

Along with the improving agricultural productivity and a rapid process of urbanization, a large amount of rural surplus labor force has moved to urban areas, becoming the largest labor flow in the world history. As a result, the historical movement of rural population has played a critical role in many development strategies (Lewis, 1954). There are lots of factors identified to explain the great migration, such as economic reforms, the widening rural-urban income gap, as well as the relaxation of the household registration system. The household registration system (*Hukou* system), which was initiated in 1958, is the main economic and institutional constraint between rural and urban areas. The purpose of the residential registration system was to support the industrialization of urban areas, meanwhile restricting the development of the countryside. Thus it was impossible for rural residents to move to urban areas at that time. Then since 1979, driven by market forces, the *Hukou* system started to reform. Yet, the number of rural migrant workers in the early 1980s was still less than 2 million (Sheng, 2000). The clearest progress toward breaking the institutional segmentation is the release of the food rationing system, and along with the widening income gap between agricultural and industrial sectors, more and more rural surplus labor force was attracted to urban areas. Consequently, the scale of migrant workers begun to take shape (Cai,2007). Based on the 1% sample from China's 1990 Census, Li (1999) estimated that the amount of rural migrants across counties and cities was around 17.5 million, accounting for 2% of the total rural population. However, in the late 1990s, a very serious unemployment scenario in urban areas emerged because of the reform of urban enterprises. To solve the severe situation and to protect the employment of urban workers, some urban governments started to adopt policies restricting the employment of rural migrants. Although the growth rate of migration was limited, the scale of migrant workers has still been expanding. Cai *et al.* (2003) find that the number of migrants reached as much as 125 million and that the migrant workers accounted for 40.7% of the total migration, using the 2000 Census data. With accelerated urbanization and the development of urban economy, this trend continued. According to the 1% population sample form 2005 Census data, the temporary migrant workers amounted to 147 million (Chen, 2007). The *Hukou* restriction has been further released and improved in 2006. In March 2006, the State Council issued "A number of opinions to solve the problems of migrant workers", which clearly put forward a series of policies to solve the problems facd by migrant workers, such as low wages, the improvement of the management of migrant workers, employment services, social security and many other aspects. Since then, migration has expanded significantly. Recent estimates from the National Bureau of Statistics show that, by the end of 2015, the total number of migrant workers was 277.47 million (Figure 1.4).

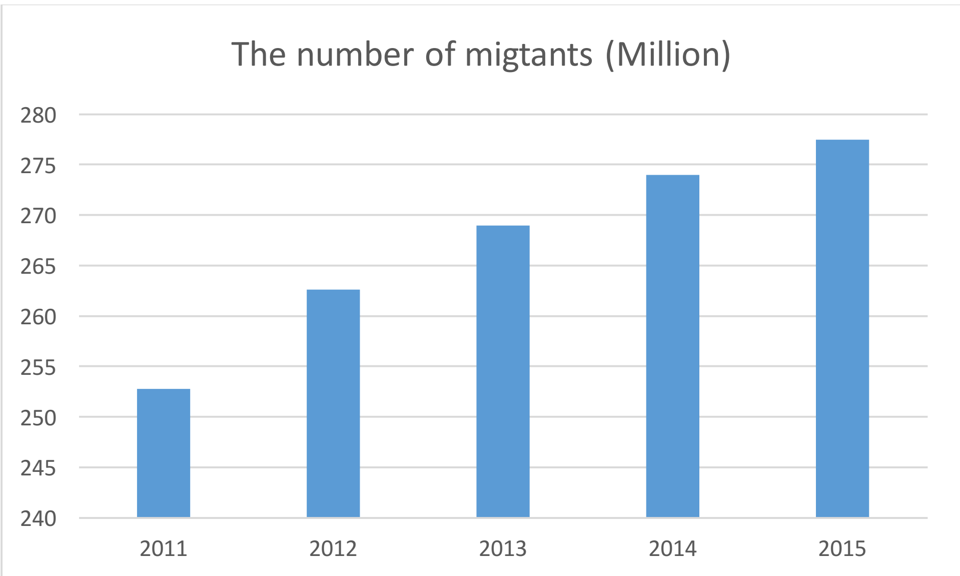

Figure 1.4 The total number of migrants from 2011 to 2015

Source: National Bureau of Statistics

Notes: The definition of migrants is rural residents who worked outside for at least 180 days.

With the increasing amount of migration, in recent years, a group of researchers have started to study the impact of the Great Migration in China, such as its effects on the economy in urban areas, as well as the positive income effect of migration on rural China[2]. For instance, the mobility of rural-to-urban migrants can not only help to accelerate urban industrialization and urbanization, but also reduce income inequality between urban and rural areas (Li et al. 1999; Cai, 2010). The existing literature has shown the effect on rural household income (Taylor et al 2003, Démurger and Li 2013, Giulietti *et al.*, 2013). The outflow of rural surplus labor contributes to the growth of income in rural areas, through two channels. First, it improves the marginal labor productivity of the labor left behind, thus increasing the average income level of the rural labor force. Second, with a higher income level and to provide support for family members left behind, the rural-to-urban migrants may send part of their income back, i.e., remittances, which may in turn increase household total income.

1.2.2. Research related to remittances

Despite the contribution that rural migrants made, they still cannot have the same rights as urban residents because of the institutional segmentation. Thus most of the migration is by individuals instead of entire households, and in most cases, the left behind are usually elderly

[2] Also researchers have found the contrasting impacts of migration on farm production (Rozelle et al. 1999; Taylor et al. 2003), labor force participation (De Brauw et al. 2002, Démurger and Li 2013), poverty (Du et al. 2005) and educational performance of children (Chen et al. 2009).

and school-aged children. Therefore, as the main aspects of economic ties between left behinds and migrants, as well as to provide support for family members, migrants allocate part of their income to remit back. In fact, the benefits of migration for the left behinds depend upon the amount of remittances (Du *et al.*, 2005). Recent estimates show that comparing to other counties, the proportion of migrants who send remittances are the highest in China (Li, 2001). As the number of migrant workers in China increases significantly, the total amount of remittances from migration has reached a considerable scale. Based on a survey in Zhejiang, Sichuan and Hunan Province, Cheng *et al.* (2005) estimated that the actual amount of remittances is around 223 billion yuan by the end of 2004. Based on the 2014 Rural–urban Migration Monitoring Survey conducted by the National Bureau of Statistics, in 2015 the total number of rural migrant workers rose rapidly to 274 million, and the total amount of remittances reached 249 billion yuan (Sheng, 2006; Cheng *et al.*, 2005). Recently, an estimation from Hu and Shi (2013) shows that the total amount of annual remittances from rural migration is more above 300 billion yuan.

With a rapid increase in both the number of rural-to-urban migrants and the amount of remittances, more and more studies shed light on the effect of migration and remittances on the left behinds. The existing literature basically focuses on the following aspects. First, on the determinants of remittances. Previous studies show that the income of migrants, gender, age, duration of stay as well as the left-behind staff will significantly affect the receipt of remittance (Lucas and Stark,1985; Germenji *et al.*, 2001; Osili, 2007). Second, regarding the role that migrant workers and remittances play on rural poverty alleviation, it has been shown that remittances can reduce the incidence of poverty in low-income families and have a positive effect on poverty alleviation in rural areas (Du *et al.*, 2005). Third, regarding the use of remittances, mainly due to the lack of representative data such as consumption, remittance income and migrant workers in the data, there are relatively fewer studies on their effect, and the existing literature is mainly based on small samples or case studies. Based on a field survey of 844 migrant families in Beijing, Li Qiang *et al.* (2008) found that remittances were mainly used to support their parents， as well as investment on children's education. De Brauw and Rozelle (2008) find that there is a difference in the effect of remittances on household expenditure behavior between poor and non-poor areas. There is a positive relationship between remittances and current consumption in poor areas, while remittances are mainly used for consumptive investment (for housing and durable consumer goods) in non-poor areas. Using rural household data collected in Jiangsu and Anhui Province, Wang (2012) finds that remittances are always correlated with higher current consumption, that is, in remittance-receiving households, food and cloth account for a higher proportion of total expenditure, while they tend to spend less on health care, housing and other expenditures than their counterpart. Based on the same data, Zhu *et al.* (2012) find similar findings, showing that remittances are mainly used for consumption while not for investment purposes. Using data from the Rural-to-Urban Migration in China (RUMiC) survey, Démurger and Wang (2016) focus on the effect of remittances on expenditures in rural areas, and find that remittance-receiving households tend to spend more on consumption-type expenditures and less on productive investment. Also they are found to favor investment which can directly improve their living (such as building new houses and spending on durable goods). Moreover, they provide evidence of negative effect of remittances on budget share for education.

1.2.3. Research on the effect of migration and remittances on Educational Investment

In theory, migration might serve as an insurance mechanism to maintain the food security of vulnerable groups such as elderly and children through remittances. As part of total household income, remittances can not only supplement income in rural China, but also increase per capita consumption and affect household consumption decisions (Taylor and Mora 2006). However, on the other hand, in an ageing context of rural China, because the lower educational attainment of migrant workers, it is not always easy for them to secure a stable and well-paid job in cities (Cai *et al.*, 2008; Démurger et al., 2009). Therefore, migration is also a risky choice. From this point of view, taking the long-term livelihood into account, rural consumers (mainly the elderly and children left behind) might reduce consumption and increase the amount of preventive savings (Meghir and Pistaferri, 2011). Moreover, the remittance of migrant workers may have special purposes, such as the maintenance of parents, subsidies for daily household and children's education, thus consumption behavior is presumed to be very different over the migration cycle.

As the most important component of human capital investment, education plays a significant role for both individuals and households. On the other hand, education investment is part of the total household spending, and is subject to family (or personal) economic constraints. Although China began to implement compulsory education in 1986 and gradually withdraw students from compulsory education, China's education has never been completely free (Hu, 2012). Especially for rural households, education investment is still a great burden. Recent statistics show that educational expenditure per capita is 305 yuan in rural areas in 2013, accounting for nearly 59.6% of consumption on education, culture and recreational services.

Thus, as a rational investment decision, like other investment decisions, investment in education will take both the returns to education and risk into account[3]. In theory, the cost of education includes tuition fees, expenditures on books, accommodation, sports and other school activities, while the opportunity cost of education mainly refers to the income children give up to get education, in particular, staying at school beyond compulsory age instead of working in the labor market. Therefore, the investment decision will be affected by family income, family property levels and other exogenous factors. Especially, with more and more parents migrating out and sending remittances back to support investment in children's' education, it is of great importance to study the impact of migration and remittances on educational investment behavior.

The empirical literature provides mixed evidence of the relationship between migration, remittances and household spending on education. A broad literature has shown that migration and remittances have a positive effect on educational investment, in Guatemala (Adams and Cuecuecha, 2010), Ecuador (Göbel, 2013), Mexico (Taylor & Mora, 2006) and the Philippines (Yang, 2008). They find that remittance transfers can relax the budget constraint of family left behind and thereby increase their spending on educational investment. By contrast, a few recent studies show that remittances may not be used to investment expenditure and have no education enhancing effect. Also the existing literature finds that the absence of parents is always correlated with adverse effects on school performance of

[3] On the other hand, however, the development of rural education is still facing lots of problems, such as the poor school quality, the large disparity in education returns between urban and rural areas, and the high dropout of junior school (Wang, 2003).

children left behind (de Brauw and Giles,2008; Lee, 2011; Chang et al., 2011; Tao and Zhou, 2012), thus remittance-receiving households may not allocate more to education. In fact, because of the lack of labor and the remittances that migrants send back, consumption behavior is presumed to be very different over the migration cycle, especially educational investment decision in migrant-sending households with children left behind. On the one hand, with the lack of labor and a decrease in child care, migration may adversely affect education decision and investment. But on the other hand, remittances can act as an insurance mechanism. Overall, the impact of migration and remittances on educational attainment and investment of children left behind is more complex and challenging to assess.

1.3. Wealth and Consumption

From the Keynesian Absolute Income hypothesis, to the basic Life Cycle theory, to the Wealth Effect theory, the study of the influencing factors of consumption gradually changes from income to household wealth. In other words, not only income, but also household wealth will have an effect on household consumption. Basically, household consumption is linearly related to current income and wealth. An empirical study of the impact of property on household consumption has found a strong positive correlation between household wealth stocks and household consumption levels (Case *et al.*,2005; Dvornak and Kohler,2007; Bostic *et al.*,2009). In particular, as the two main components of household wealth, more and more scholars focus on the effect of financial assets and real estate on household consumption. Since financial and housing wealth are different in terms of liquidity, measurability and capital gain, their effects on consumption may also be diverse. And so far, the existing studies on financial/housing wealth and consumption provide mixed evidence (Campbell and Cocco,2007; Sierminska and Takhtamanova ,2007; Bostic *et al.*,2009).

In theory, the accumulation of household wealth has two main sources: savings from current income and changes in assets valuation. In the actual practice, the beginning of the 2000s has witnessed a dramatic increase in Chinese household income as well as substantial changes in assets prices, notably the real estate prices, which indicates these two sources change together. Given the unprecedented changes in household wealth, assessing the correlation between household wealth and consumption is of great importance. Also, household consumption may respond differently to different components of wealth. But systematic evidence is missing on how consumption is affected by household wealth, as well as wealth components in China.

1.4. Study on Poverty and Poverty alleviation

The problem of consumption has always been a concern of the economic growth. Besides studying its influencing factors and measuring the differences in well-being between families, consumption is also an important measurement to measure the incidence of poverty. The alleviation of poverty is a long-term task for developing countries in the process of economic development, as well as an important research topic in development economics. According to the World Bank's latest statistics, more than 800 million people around the world live in poverty in 2015, of which poor population in rural China accounts for nearly a quarter. In 2015, the United Nations Conference proposed the "Sustainable Development Goals" (SDGs), one of which is to "eliminate poverty in all its forms everywhere" by the end of 2030. At the same time, the Chinese government has also set a goal to eliminate absolute poverty by 2020.

1.4.1. Fighting rural poverty

Due to the large income disparity between rural and urban areas, poverty is considered to be primarily a rural phenomenon and dominates the scene (Yao et al., 2014; Zhang and Wan, 2006). The Chinese government goes a long way toward alleviating poverty.

In 1986, to eliminate rural poverty, the Chinese government established the Leading Group for Economic Development in Poor Areas (LGEDPA) to formulate guidelines for economic development in poor areas, which was renamed as The State Council Leading Group Office of Poverty Alleviation and Development Government in 1993.In 1994, to lift the remaining 80 million poor population in rural areas out of poverty, the government announced the Baqi (8–7) plan and carried out organized, planned and large-scale poverty alleviation program. During the period 1994-2000, the three main targeted poverty investment programs included a subsidized loan program (tiexi daikuan), a public program called Food-for-Work (yigong daizhen) and a budgetary grant program (fazhan zijin) (Park et al.,2002). The goal of these programs is not only to transfer funds or resources to the poor, but also to promote economic development in poor counties and increase income growth to lift the poor out of poverty. The reduction of rural poverty has been impressive during this period. According to official statistics, during 1986 to 1999, the number of poor residents in rural areas fell significantly from 131 million to 40 million.

As the incidence of poverty is concerned, poverty reduction has also been dramatic since the economic reforms (Table 4). Based on the earliest poverty standard (Absolute Poverty Line), the incidence of rural poverty fell from 30.7% in 1978 to 1.7% in 2007. Since 2008, the national poverty line was further raised to 1196 yuan (also called Low Income line), and the poverty rate fell from 10.2% in 2000 to 2.8% in 2010 by this standard. In the year 2010, The State Council Leading Group Office of Poverty Alleviation and Development Government again amended the poverty line to 2,300 yuan (known as the New Poverty Line), and according to this national standard, the incidence of poverty fell from 17.2% in 2010 to 5.7% in 2015. Unsurprisingly, poverty incidence declined substantially, no matter which poverty line is used.

1.4.2. Consumption and Poverty

The importance of consumption research to poverty alleviation can be seen from the estimation of national poverty lines. Following Ravallion (1994), the setting of poverty line starts from the definition of a food poverty line and then evaluates the basic nonfood demand. The first official poverty line was developed by the National Bureau of Statistics in 1986, defining rural residents with per capita net incomes below 206 yuan as absolutely poor. To compare the amount of the poor with other countries in the world, the government announced a low-income standard of 880 yuan in the year 2000. Again, the setting method is based on the consumption expenditure of rural residents, that is, using the food poverty line in 1997 and assuming that the budget share of food consumption in poor households accounts for 60% of the total consumption expenditure (i.e., the Engel coefficient is 0.6). Subsequently, since 2008, the government amended the poverty line to 1196 yuan, which is also set on the consumer demands (especially food consumption demand). In 2010, the poverty line was again adjusted to 2,300 yuan, according to the current situation of poverty in rural areas and the poverty alleviation goal. The setting method is the following. Rural poverty line should be sufficient to meet the needs of food and healthy consumption, and meet the demand of non-food consumption which is equally important, with basic housing as a basic condition. In other words, without serious or unexpected disasters, this new rural poverty line can guarantee basic necessities including food, clothing, health and other consumption. Overall, consumption patterns are the dominant measurement of the evaluation of poverty lines.

However, as can be seen from Figure 1.5, it is worth to note the downward trend in the incidence of poverty between 2010 and 2014. Although the number of poor has been drastically reduced, the reduction of the poverty rate has gradually slowed down from 2010 to 2014, indicating that the difficulty for poverty alleviation is increasing. It is thus important to understand the effect of anti-poverty policies in rural China.

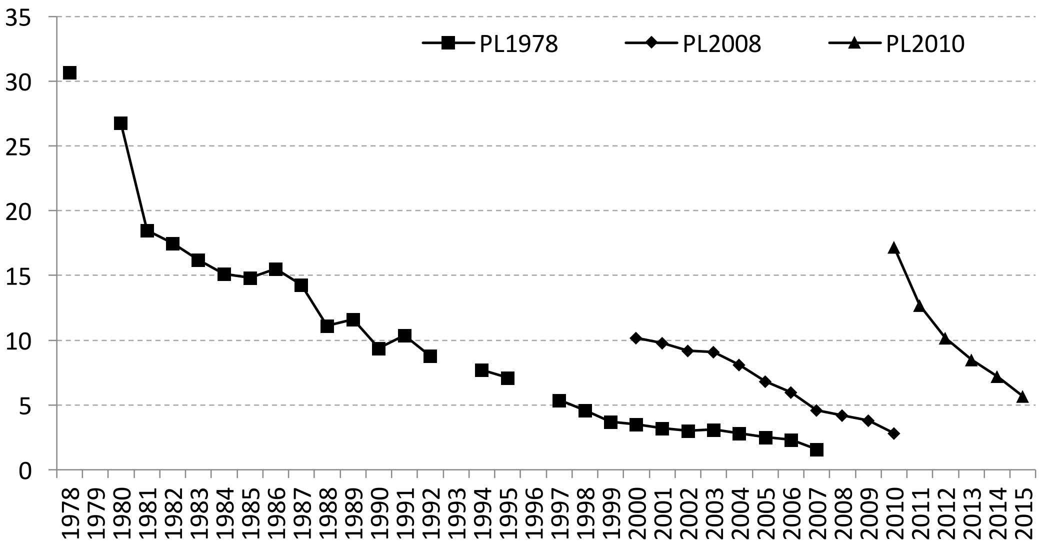

Figure 1.5 The incidence of rural poverty between 1978 and 2015

Source: National Bureau of Statistics and author's calculation.

1.4.3. China’s Rural Minimum Living Standard Guarantee Programme

The poverty lines are set based on the consumption of rural residents, therefore, consumption is an important indicator to measure the degree of poverty. Battling rural poverty is a long-term task for the Chinese government. China has set the goal to eliminate poverty by 2020, and to achieve this goal, the government is implementing the “Precise Poverty-Alleviation Strategy” (Jingzhun Fupin). The key of this strategy is the precise identification of the poor. In practice, the Poverty Alleviation policy and the Rural Minimum Living Standard Guarantee Programme (rural dibao program) are the two main anti-poverty packages. Nowadays, more than 600 million people in China have been lift out of poverty. And success in battling rural poverty clearly proves the great effect of these two programs toward poverty alleviation in China. In particular, the rural Dibao program is treated as an insurance program (*doudi*). Despite its great importance, the study of the targeting effectiveness of this program is still scarce. Therefore, based on the important role that the rural Dibao program plays in the anti-poverty work, we try to evaluate the targeting performance of this program.

On basis of the Regulations on the Minimum Living Standard Guarantee Program>, the identification of the beneficiaries must meet three basic conditions: residents who hold local rural Hukou; households with per capita net income lower than the local income threshold, and the household wealth in line with the regulations of the local government, that is, the rural beneficiaries are the rural residents whose per capita net income is lower than the income threshold set locally at the county level. However, in practice, additional information about the household is also used to evaluate eligibility, such as household assets, the presence of household members who are unable to work, illness or disable, as well as the presence of natural disasters (the Ministry of Civil Affairs). Regarding the application process, according to income and other additional information, families first apply to the township government. Then, the township re-checks the applicants, submit the application to the county government, and waits for the approval process. Clearly, the most important procedure in the application process is the identification of eligibility carried out by the local leaders. Although income is the only criterion, it is difficult to accurately measure household income in rural areas[4]. In practice, in addition to household's income, village leaders make use of other information in local implementation practices, such as demographic composition, household assets or some sort of natural disaster. Thus, whether the rural dibao program can really play an important role in poverty alleviation highly depends to what extent the rural dibao program targets the poor. The targeting performance of this program is not only directly related to achieving the goal of eliminating poverty by 2020, but also to the realization of the national well-off strategic goal.

1.5. The structure of the dissertation

On the basis of the existing literature, we are well aware that many factors may affect consumption, such factors including not only those related to the tremendous changes in the labor market, i.e., the increasing number of rural to urban migration, but also unprecedented

[4] In rural areas, household incomes are more likely to be in the form of farming. However, with an increase in the number of migrant workers, other forms of income such as wages and remittances are becoming a large proportion of household income. However, they are difficult to be grasped or screened. Moreover, there is time difference between survey-based incomes and those used in identifying eligibility (Chen et al., 2006), which may also cause measuring errors.

changes in the accumulation of household wealth. However, until now, systematic evidence is missing on how consumption in China is affected by migration and by household wealth. Meanwhile, regarding rural household consumption, another related issue, consumption poverty, is also discussed, especially the role that China's Rural Minimum Living Standard Guarantee Program plays in alleviation poverty. But so far less has been said on the targeting performance of this poverty alleviation policy. With the knowledge of the importance of consumption study in rural China, in this dissertation, we choose consumption issues as an entry point and pay special attention to its influencing factors.

The labor market in China has gone through tremendous changes over the last three decades of economic reforms. One of the most dramatic changes over recent years is a rapid increase in the number of rural-urban migrants. With such population movement, the existing literature has provided mixed evidence about the influencing factors and the impact of the Great Migration. However, the effect of migration on the individuals left-behind is complex and challenging to assess, especially how consumption and educational investment are affected by migration in rural China. So we first examine the effect of migration and remittances on educational investment in rural China. Since the theoretical channels through which migration may affect investment in education are diverse with remittances, we especially account for the differential effects of migration and remittances on educational investment.

Afterwards, another related factor that may affect household consumption is wealth. Given the unprecedented changes in household wealth in recent years, we focus on the strength of the correlation between household wealth and consumption in China and its changes between 2002 and 2013. In particular, because households may respond differently in terms of consumption to various components of wealth, we also estimate the differential effects of financial and housing wealth on household consumption.

Furthermore, lot of studies have highlighted the declining trend of the incidence of rural poverty, but fewer have paid attention to the targeting performance of the poverty alleviation policy, the rural Dibao Program. As one of the most important strategy, China's Rural minimum living standard guarantee programme (Dibao Program) aims to provide cash transfers to all households with incomes below the Dibao lines set at the county level. So in practice, the rural Dibao program should not only well target all the eligible households, but also has well-functioning checks and balances, to achieve the "perfect Dibao targeting". Thus, the targeting performance of China's rural Dibao program in practice highly depends on the targeting accuracy of this program. Therefore, we try to evaluate the targeting effectiveness of the rural Dibao program.

The remainder of this dissertation is organized as follows:

In Chapter 2, the central target is to estimate the impact of migration and remittances on school decision and educational investment in rural China. To assess their effects, we employ different types of dataset and different methodologies. To examine the impact of migration and remittances on school enrollment, based on the child-level database aged between 7~18, we use a binary model, where the dependent variable is children's school decision and the independent variables include household type, We estimate a Tobit model of household expenditure on education, using the household-level database with at least one child at school in 2013. To solve the endogeneity problem of migration decision, as well as the receipt of remittances, we employ instrumental variables.

In Chapter 3, we consider the relationship between household wealth and consumption in China, and distinguish the differential effects of financial and housing wealth. Since a number of households in the dataset failed to report the exact value of their financial wealth or reported no financial assets at all, we predict their financial assets based on a specific function. Then we employ a standard approach that relates household consumption to wealth and wealth components, controlling for income and other socioeconomic characteristics.

In Chapter 4, on the basis of the rural household survey data in the year 2013, we evaluate the targeting performance of the rural Dibao program. Because the traditional income identification criterion reveals quite large targeting errors, we then propose a new selection criterion, the multi-dimensional identification criterion, to evaluate the targeting effectiveness of the rural Dibao program.

2. Migration, Remittances and Educational Investment in Rural China

2.1. Introduction

Rapid demographic and economic changes have been taking place in China since 1978. One of the most important changes in recent years is a rapid increase in the number of rural-urban migrants. Two main reasons are causing this so-called Great Migration: one is the economic reforms implemented in China since the late 1970s, which have improved the agriculture productivity in rural areas and liberated a large amount of rural surplus labor (Knight et al., 2010); the second is the release of administrative controls (Hukou system) on rural-urban labor mobility. Before the economic reforms, there was a significant segregation between urban and rural residents, which restricted their mobility. As a result, rural-urban migration in the early 1980s amounted to less than 2 million people. Then since the early 1990s, the food rationing system, which restricted the rural-urban mobility, was abolished, and the Hukou registration system was gradually released as well. On the other hand, along with the rapid development of urban enterprises, a huge income gap appeared between non-farm and farm employment, which attracted the rural surplus labor force to migrate to urban areas (Cai, 2007). Recent estimates from the National Bureau of Statistics report that the total number of migrants reaches as far as almost 274 million in 2014, indicating that there is one migrant among every six Chinese people. A large number of studies have analyzed the consequences of the Great Migration on the social and economic changes in China in recent years. Among others, they show that migration accelerates urban industrialization and urbanization and helps narrowing the income gap between urban and rural areas and coordinating the urban-rural development (Cai and Wang, 2003). Another set of studies have explained the impact of migration on the natives' labor market outcomes in the destination cities (Combes et al., 2015), the effect on rural household income as well as on the left-behinds in rural areas (Taylor et al., 2003; Giulietti et al., 2010; Démurger and Li 2013;). Generally, the *Hukou* system divides rural children into three parts: local children with parents stayed in rural areas, migrant children with migrant parents in urban areas and children left behind in rural areas with parents migrated to urban areas. With more and more individuals migrating to urban areas, the number of children left-behind in rural China is dramatically increasing (Démurger and Xu, 2015). Based on the 2010 Census, recent estimates report that the number of left-behind children in rural China is over 61 million, accounting for 21.88% of the total children in China. With such a large number of children left-behind, the impact of the Great Migration on left-behind children is worth to study.

Given the importance of migrants, there is little doubt that the mobility of the rural surplus labor contributes to the income growth in the rural areas, which will in turn affect the household consumption patterns and investment decisions. As an important component of household investment on human capital, expenditures on education play a vital role in human capital accumulation and improvement. And along with the economic development and income growth in rural areas, the level of education has increased. However, there still exists disparities in schooling between rich and poor areas. For instance, children from poor households are less likely to complete junior high school. With a particular focus on schooling, this paper studies the effects of migration and remittances on school enrollment and educational investment in rural China.

The main contribution of this paper is twofold. First, unlike previous studies using small scale databases, this research relies on the most recent data from the China Household Income Project 2013, which was conducted in 12 provinces and 2 province-level municipalities in China, covering around 10,000 rural households and 39,065 individuals. The data contains detailed information on individual characteristics, household income as well as consumption components in rural China, which allows us to measure the effect of migration and remittances on investment in education. Second, migrants may affect educational investment in ways that remittances do not adequately capture (Taylor and Mora, 2006). As emphasized before, the mechanisms through which migration and remittances influence educational investment are not the same. For instance, remittances may affect schooling mainly through an income effect, while migration may have an impact on consumption behavior or habits of the left-behinds. In this paper, we specifically account for the differential effects of migration and remittances on educational investment.

The structure of this paper proceeds as follows. Section 2 reviews the available literature. Section 3 describes the data from rural China and presents some descriptive statistics. Section 4 shows the empirical strategies used in this paper. The results are presented in Section 5 and Section 6 provides tentative explanations regarding our findings. Section 7 concludes.

2.2. Migration, Remittances and Education

Given the increasing trend of rural to urban migration, a growing body of literature are studying the impact of migration in the original areas. In terms of the effect of migration on rural areas, researches show contrasting impacts on farm production (Rozelle et al., 1999; Taylor et al., 2003), labor force participation (Démurger and Li, 2013), poverty (Du et al., 2005) and educational performance of children (de Brauw and Giles,2008; Chen et al.,2009; Lee, 2011; Chang et al., 2011; Tao and Zhou, 2012). In recent years, with more and more children left behind in rural areas, a group of researchers have raised concerns about the potential effects of migration on these school-aged children.

The three theoretical channels through which migration may affect investment in education are diverse and of opposite aspects, which leads to an underdetermined net effect. First of all, the loss of household labor or the absence of parental migrants may negatively affect educational performance, and also educational investment. The mobility of labor may impose a social cost on left-behinds (Démurger, 2015), and due to the lack of labor, children left-behind have to spend more time on agriculture than school, which may restrict their access to school. Furthermore, parental absence, which is always consistent with a decrease in child care and supervision, can have disruptive effect on children's school preference and household investment in education (Hanson and Woodruff, 2003; Mansuri, 2006; McKenzie and Rapoport, 2011). For instance, McKenzie and Rapoport (2011) find that the emigration from Mexico to the U.S adversely affect school enrollment and attainment of older children left behind. Also some studies documents that children left behind of migrant mothers have more difficulties in school than those left behind by fathers (Battistella and Conaco, 1998). As for China, studies investigating the effect of parental migrants on school performance provide contrasting results. Some scholars report that the absence of parental migrants may have multiple adverse effects on school enrollment and educational performance (de Brauw and Giles,2008; Lee, 2011; Chang et al., 2011; Tao and Zhou, 2012), which is mainly due to the less supervision or less emotional support (Hu, 2012). Kong and Meng (2010), for example, employ RUMiC data and find that the absence of parents has a negative effect on children's educational performance. Tao and Zhou (2012) find a negative correlation between parental migrants and school performance of left-behind children, and the adverse effect increases with parents leaving for a longer period of time. Based on China Health and Nutrition Survey (CHNS), Lee (2011) and Chang et al., (2011) also support that parental migration has a negative impact on children's schooling. Wang (2014) finds that the parental absence from home adversely affect children's school enrollment. By contrast, using data from a survey of 36 primary schools in 12 townships in Shanxi Province, Chen et al. (2009) employ difference-in-difference method to estimate the effect of migration on school performance but they find no statistically significant negative effect. In contrast, they provide evidence that the educational performance improves in households with father migrated.[5] The existing studies provide evidence of contradicting results on the effect of migration. One possible reason is that they all ignore the effect of remittances, which may lead to an opposite direction.

Second, migration can increase income through remittances, which may have a direct impact on children's education. On the one hand, as part of the total household income, remittances sent back home increase household income and ease household liquidity constraints, and thereby decrease child labor and affect the educational investment decision. On the other hand, since most migrants in China are unskilled workers, who are less educated relative to local workers (Démurger et al., 2009), it is not easy for migrants to secure a stable and well-paid job in cities. Studies find that most rural migrants work primarily in the informal sector (Démurger et al., 2009), facing poor and unsafe working conditions. They may be confronted with unemployment risk at destination. As a result, considering the long-term livelihood, the

[5] Beside school achievement, a significant negative effect is also found in terms of the effect of migration on food and nutrition (Gao et al 2010; Kong et al 2010).

left-behinds (mostly elderly and children) may decrease consumption including education expenditure and accumulate saving. Recently, some studies have investigated the relationship between remittances and household education consumption decision and found a positive effect in most developing countries, showing that households who receive remittances spend more on education, in Ecuador (Göbel, 2013), the Philippines (Yang, 2008), Mexico (Taylor et al., 2006), Guatemala (Adams and Cuecuecha, 2010) and Kenya (Hines, 2015). Using the Working-Leser Model, Adams and Cuecuecha (2010) analyze the impact of migrants' remittances on household consumption and investment decisions in Guatemala and find that households receiving international remittances spend less at the margin on food consumption, and instead spend more at the margin on education and housing. Based on the same model, Göbel (2013) analyzes the impact of remittances on household's budget allocation in Ecuador and provides evidence of a positive relationship between remittances and spending on education, showing that households receiving remittance have a stronger motivation to accumulate human capital. Hines and Simpson (2015) develop a theoretical model predicting remittances as a mechanism to transfer migrants' income, which independently affects household consumption patterns. They find that increasing remittances enhance educational investment in Kenya. As far as China is concerned, however, the study of the effect of remittances on educational investment has been rarely documented. To the very best of my knowledge, because of data limitation, only three published papers examines the role that remittances plays in educational investment. Hu (2012, 2013) finds that although the absence of parental migrants has a large negative effect on educational achievement, the effects of remittances can compensate part of the loss. Démurger and Wang (2016) show that households received remittances allocate a smaller share of their budget to education than their counterpart.

Third, by increasing the prospect of future migration for children left-behind, which is determined by the perceived returns to education in China, migration may have an indirect effect on educational investment in opposite ways. Stark et al. (1997) shows that migration can lead to higher level of human capital in the source country, so households may invest in education of certain members, who then migrate and earn a higher wage than they would otherwise. Thus there is a possibility that households may increase their spending on education, if the perceived returns to education are high. For instance, Kochar (2004) provides evidence that the higher urban returns on education, the higher children's school enrollment in rural India. Yet the lower returns to education in rural China may push children left-behind out of school. Then education may be viewed as a consumption good rather than an investment good (Song et al., 2006), and households may reduce their spending on education.

2.3. Data

2.3.1. The database

The data employed for this study comes from the China Household Income Project conducted by the China Institute of Income Distribution, with the reference year of 2013 (CHIP 2013). The households surveyed were drawn from the sampling framework of the regular household survey annually conducted by the National Bureau of Statistics of China. The field survey includes detailed information about the demographic characteristics, the household structure and employment, while the information about items of income and expenditure is provided directly from the NBS regular survey. The survey covers 12 provinces and 2 province-level municipalities in China, with approximately 10,000 rural households and around 39,065 individuals, scattered over eastern (Beijing, Liaoning, Jiangsu, Shandong, Guangdong), central

(Shanxi, Anhui, Henan, Hubei, Hunan), and western (Gansu, Sichuan, Chongqing, Yunnan) China. After cleaning outliers on the household data on expenditure, the final sample is 9,702 households.

As the particular focus of this paper is on the impact of migration and remittances on educational investment, the definitions of migrant-sending and remittance-receiving are worth to be noted. The definition of migrants used in this paper is rural residents who worked outside for at least 180 days or were working outside the county surveyed in 2013. A migrant-sending household is defined as a household with at least one migrant, while a remittance-receiving household is a household has received remittances in 2013 (following Démurger and Wang, 2016). Migrant-sending households and remittance-receiving households do not perfectly match, indicating that there are some rural households without migrants that receive remittances. In fact, these remittances may be contributing to household income, but the sources of remittance cannot be identified since we cannot capture whether the transfers were received from institution or economic assistance or other relatives. Concerning that the monetary values for remittances may be subject to some specific aspect, thus we exclude these households. Remittance-recipient households are then defined as money received from someone who did not lived in the household in 2013.

To investigate the differential contributions of migration and remittances on educational investment, the household sample is divided into 3 groups: non-migrant sending and non-remittance receiving households, migrant-sending and remittance-receiving households, migrant-sending but non-remittance receiving households. As Table 1 shows, 2,459 rural households send migrants and receive remittances, accounting for 27.54% of the total number of households; 1,733 households (19.41% of the total) are migrant-sending but do not receive any remittance; and 4,738 households (53.06%) do not send any migrant or receive remittance.

Table 2-1 **Distribution of households**

	Observations[6]	Share
Non-migrant and non-receiving	4,738	53.06
Migrant-sending and remittance-receiving	2,459	27.54
Migrant-sending but non-receiving	1,733	19.41
Total	8,930	100

Source: Author's calculation from 2013 China Household Income Project.

The summary statistics for income and income shares are listed in Table 2. Compared to non-migrant sending households, the total household income and per capita income[7] are much smaller, either in the migrant-sending households with or without remittances. It is clear that the average net income per capita is the lowest in households with migrants and remittances (6,902 Yuan), which is just 54% of that in households without migrant or remittance (12,698 Yuan). It may indicate that less affluent families are more likely to send migrants and receive remittances. To understand it better, we also compare the distribution of households among each income per capita quartile and find evidence that the proportion of households that send migrants and receive remittances decreases from the bottom to the top income groups. In

[6] If we restricted household samples to households with positive educational expenditure, the distribution of the total samples is similar.

[7] As for the definition of income and expenditure per capita, we impose income to be for all the members in the household, including migrants. In contrast, expenditures are just for permanent residents, since the consumption of migrants is not counted into the total expenditure. So per capita expenditure (excluding migrants) is defined as per capita expenditure of each permanent resident.

other words, compared to richer households, poorer families tend to send migrants out with the intention of sending remittances back to improve the welfare of the whole family. In addition to household income, the shares of income components shown in Table 2 further reflect that transfer income is an essential component in remittance-receiving households. The corresponding share of remittances in total household income is around 35.54% in migrant-sending and remittance-receiving households. By contrast, in households without remittances, the share of transfer income is much smaller.

Table 2-2 **Summary statistics by group-income and income share**

	(1)	(2)	(3)	T-test	T-test
	Non-migrant non-receiving	Migrant receiving	Migrant Non-receiving	(1)VS(2+3)	(2)VS(3)
Total net income(Yuan)	39,389	29,018	42,191	***	***
Net income per capita (Yuan)	12,698	6,902	10,990	***	***
Net transfer income(Yuan)	3,145	10,246	1,,717	***	***
#remittance(Yuan)	0	8823	0	***	***
Share of transfer income(%)	7.15	43.87	9.81	**	***
#Share of remittance(%)	0.00	35.54	0.00	***	***
Observations	4,738	2,459	1,733		

Notes: The last column shows the significance level of mean differences between different groups of households (NO: non-significant; *: significant at 10%; **: significant at 5%; ***: significant at 1%).

Source: Author's calculation from 2013 China Household Income Project.

As with expenditures, household consumption expenditure is aggregated into five consumption categories (following Démurger and Wang 2016): 1) food (including food, clothing and miscellaneous goods and services); 2) durable goods (including expenditures on facility and services, communication and transportation); 3) housing; 4) education[8] (including tuition[9], textbooks, accommodation or other school-based fees on children, entertainment, and cultural activities); and 5) health care.

Table 2-3 **Summary statistics by household expenditure and expenditure budget shares**

	(1)	(2)	(3)	T-test	T-test
	Non-migrant non-receiving	Migrant receiving	Migrant Non-receiving	(1)VS (2+3)	(2)VS(3)
Total expenditure	28,975	23,944	31,649	***	***
Household Expenditure per capita	9,333	9,845	14,123	***	***
Education expenditure	2,929	2,219	3,248	**	***
Budget share for food	47.25	48.39	45.66	NO	***
Budget share for durable goods	15.37	15.16	16.84	**	***
Budget share for housing	21.81	21.00	21.39	**	NO
Budget share for medical care	7.38	7.36	6.86	NO	**
Budget share for education	8.19	8.10	9.25	NO	***

Notes: "Household Expenditure per capita" calculated here is the per capita expenditure excluding migrants in the households.

Source: Author's calculation from 2013 China Household Income Project.

Based on these consumption items, Table 3 provides a comparison of expenditure and average budget shares for the four household groups. Consistent with the income results, the consumption results also reflect that total household expenditure is much lower in remittance-receiving households than their counterpart, i.e. households without remittances. Household expenditure per capita listed in the table reveals that it is the highest in migrant-

[8] Expenditures on durables and housing are treated as "consumptive investment" (de Brauw and Rozelle 2008), while expenditures on education and health care are counted as human capital investment.

[9] In CHIP data, for each household, we can only get access to total educational expenditure.

sending households without remittances, and the smallest in migrant-sending and remittance-receiving households. This table also reveals that households that send migrants and receives remittances spend less on education than those migrant-sending households without remittances (8.10% against 9.25%), and the gap is significant at 1%. Since remittance-receiving households are less affluent and with more elderly left-behinds, so they might be more likely to spend money on food or medical care rather than on education.

3.2. School Enrollment

In order to capture the impact of migration and remittances on school enrollment, we restrict the samples to a child-level database with children aged between 7 and 18 years, who should attend primary school (aged between 7~12), junior secondary school (aged between 13~15) or senior high school (aged between 16~18). The final child-level sample is 4,863.[10]

[10] Table A.1 (Appendix) illustrates the descriptive statistics of children aged between 7~18 and their corresponding household-level characteristics. As shown in this table, households without migrants or remittances tend to have fewer children and fewer old dependent people, while the average education level of household adult members and the proportion of households with at least a member with higher education (above high school education) are much higher. By contrast, although with more labor in migrant-sending households with remittances, there are more children and old dependent people, as well as less households' assets.

Table 2-4 Differences in school enrollment in children aged 7-18

	Non-migrant non-receiving	Migrant receiving	Migrant Non－receiving	Total
At school(% of children)	92.65	84.62	83.42	88.32
Gender				
Boy	91.80	83.88	82.93	87.51
Girl	93.60	85.53	84.01	89.27
Age				
7～12	96.98	95.08	95.85	96.16
13～15	95.12	94.79	88.68	93.38
16～18	82.71	59.13	62.37	70.80
Region				
East	93.58	80.95	84.74	89.37
Centre	91.30	87.15	83.91	88.13
West	92.85	83.43	80.65	87.45

Source: Author's calculation from 2013 China Household Income Project. Child-Level database with children aged between 7 ~18.

Among all the children aged 7~18, the enrollment rate in rural China in 2013 is about 88% [11] .Table 4 compares school enrollment across different types of households. In households without migrants or remittances, over 90% of children attend school while in migrant-sending households without remittances, the enrollment rate is almost 10 percent lower. In terms of the gender difference, enrollment rates are 89.27% for girls while 87.51% for boys, with a similar tendency in each type of households. Before discussing the age disparities in this table, the Nine-year Compulsory Education System in China is worth to be explained. Following most developed countries, China's government made education

[11] According to the 2014 Statistics of National Education Development Statistics>, the net enrollment rate for primary school in China is 99.81%, while the gross enrollment rate for high school is 86.%. However, until now there are no official statistics on the enrollment rate for rural children.

compulsory and free since 1986, stipulating 9 years of compulsory education including six years of primary school and three years of junior secondary school. Consequently, the enrollment rate is much higher in lower age groups, with over 96% of children aged between 7~12 attending school and for the age group 13~15 over 93% of children enrolled in school. On the other hand, the enrollment rate is only 70.80% in the upper age group 16~18, indicating that nearly 30% of children drop out of high school. The difference of school enrollment between different household groups is largest in this older group. The comparison shows that 82.71% of children aged between 16~18 attend school in households without migrants or remittances, whereas the high school enrollment rate is only 59.13% in households with migrants and remittances. In addition, the comparison of three regions reveals that the total school enrollment is the lowest in households in western areas and highest in eastern areas, which is consistent with the differential economic growth among the three regions.

2.3.2. Educational Investment

Table 5 documents the differences in educational expenditures, using household-level database with at least one child at school in 2013[12]. The comparison shows that relatively to non-receiving households, remittance-receiving households have more children enrolled at school. However, expenditures on education are much lower in remittance-receiving

[12] The summary statistics of household characteristics in households with at least one child at school are displayed in Table A.2 (See Appendix).

households. Educational investment per child [13] is the lowest in migrant-sending and remittance-receiving households (2,341 Yuan per child), and the highest in households without migrants or remittances (4,406 Yuan per child). When it comes to the budget share of education, in households with migrants and remittances, only 13.21% of total expenditure are allocated to education, whereas in households without migrants or remittances, the corresponding budget share reaches 14.89%.

Table 2-5 The differences in education expenditures in children enrolled in school

	(1)	(2)	(3)	T-test	T-test
	Non-migrant non-receiving	Migrant receiving	Migrant non-receiving	(1)VS (2+3)	(2)VS (3)
Number of children at school	1.35	1.41	1.31	NO	***
Education expenditure	4,406	3,020	3,981	***	***
Educational expenditure per child	3,490	2,341	3,284	***	***
Budget share of education	14.89	13.21	14.45	**	*
Observations	1,902	1,090	795		

Notes: Household-level database with at least one child at school in 2013.

Source: Household-Level database with at least one child at school in 2013.Author's calculation from 2013 China Household Income Project.

2.4. Methodology

2.4.1. Measuring the impact on school enrollment

Based on the child-level database aged between 7~18, we use a binary model (1) to estimate the effect of migration and remittances on educational decision:

[13] Education expenditure per child is defined as educational expenditure on each child who was at school in 2013.

$$\text{School}=\beta_0+\ \beta_1 Household\ +\beta_2 Child\ +\ \beta_3 X_h\ +\ \beta_4\text{Household Asset}+\beta_4\text{Province}+\ \mu \tag{1}$$

where the dependent variable *School* is 1 if the child is enrolled in school, and 0 otherwise. *Household*, the main variable of interest, is the household type as defined above. Other explanatory variables include a vector of child-level characteristics($Child$), such as age, gender, age-group and age-gender category[14]; Household characteristics, X_h, contains not only the average age of adults, the average education of adults, but also household composition variables such as the number of children below age 6, the number of children aged between 7 and 12, the number of children aged between 13 and 15, the number of children aged between 16 and 18, the number of household members aged between 19 and 55, the number of household members aged between 56 and 65, the number of elderly (over 66 years old),whether the household has member(s) with disability or chronic illness[15]. A dummy variable "*Having at least a member with higher education*" indicates whether the educational decision may be affected by the most educated household member[16]. Since the higher investment in education may be due to a higher level of wealth, we also include household wealth*, Household Asset*, measured as the logarithm of housing value and total

14 "Age-Group" is a dummy variable, referring to children aged between 16~18. While "age-gender category' is 1 if the child is a boy aged 16~18, 0 otherwise.

15 We expect that in these households, people would tend to have higher health care expenses, which will in turn affect spending on education.

16 Hines and Simpson (2015) provide evidence that a highly educated family member in the household has a stronger preference for investment in education.

agricultural land[17]. *Province* stands for provincial dummies that account for unobservable variables which can affect the effects of migration and remittances at provincial level.

2.4.2. Measuring the effect on educational investment

Another question relates to whether migration and remittances have differential impacts on household educational spending on children at school. We then estimate a model of household expenditure on education. In the database, nearly 10% of households have a value of zero for this variable, which suggests that these households, with at least one child at school, spend zero on education in the survey year. An OLS model assumes that the dependent variable is normally distributed, which may be not appropriate here since the educational investment is censored at zero. To take the censored spending on education into account, a Tobit Model is employed[18]. The model is specified as follows:

$$Y_i^{*}=\beta_0+\ \beta_1 Household_i+\ \beta_2 X_{ij}\ +\ \beta_3 Household\ Asset_i+\ \beta_4 \text{Province}\ +\ \mu \qquad (2)$$

$$\mathrm{Y}=\begin{cases} Y_i^{*}, & \text{if } Y_i^{*}>0 \\ 0, & \text{if } Y_i^{*}=0 \end{cases} \qquad (3)$$

---

[17] However, people may be worried that household incomes and children's high school attendance are jointly determined by some unobserved household characteristics. To reduce such endogeneity concerns, the log of household house value is included in the equation to represent the income effect. Another benefit of using house value instead of current household income is that house can represent a relatively long term economic status

[18] It should be noticed that because the dependent variable is the logarithm of educational investment, so we rescaled expenditure on education so that the minimum value is one instead of zero.

Where Y_i^* is the latent variable and Y is the observed variable. The main dependent variable Y_i, the logarithm spending of household *i* on education. Right hand variables are almost the same as in the model for education decision (see above), except that we also control the number of children at school in this estimation.

Following the method proposed by McDonald and Moffitt (1980), we can further decompose the estimated coefficients into two marginal effects: One is the unconditional marginal effect, the other is the conditional marginal effect on the fact that the dependent variable is already over zero. The marginal effects can be shown as follows:

$$\frac{\partial E(Y)}{\partial X_j} = f(z)\beta_i/\sigma \tag{4}$$

$$\frac{\partial E(Y|Y_i^*>0)}{\partial X_j} = \beta_i\left[1 - \frac{zf(z)}{F(z)} - f(z)^2/F(z)^2\right] \tag{5}$$

Where $z = \frac{X\beta}{\sigma}$, f is the normal density, F is the cumulative normal distribution function, and σ is the standard error of the error term μ.

2.4.3. The endogeneity of migration and remittance decisions

Mainly due to the reverse causality, the potential problem related to this research is the endogeneity of migration decision as well as that of the receipt of remittances, which could lead to biased estimates of the impacts of migration and remittances on educational investment in the Tobit model. Since migration is a selective process, migration and remittance decision may be related with some unobservable factors which also affect the educational decision. For instance, those poor households may prefer to send adult members out for the explicit reason to increase household income for children's education. In addition, there may exist omitted variables which can influence both migration/remittances and consumption patterns. For example, natural calamity such as crop failure caused by drought, may cause adult household members migrate out and school aged children drop out of school or decrease educational investment at the same time. To solve this endogeneity problem, we employ instrumental variables, which are correlated with migration or remittances decision, but not related to household spending on education. Previous studies demonstrate the roles that social networks (Munshi, 2003; Tylor and Mora, 2006; Adams and Cuecuecha, 2008; Hines, 2015), distance to the railway station (Adams and Cuecuecha, 2013; Hines, 2015), the fraction of households receiving remittance (Adams and Cuecuecha, 2013) play in the decision to migrate or remit.

Following the existing literature, we construct several instrumental variables. The fraction of households receiving remittance in the original village excluding household *i* is used as an instrumental variable for the migration decision[19]. The assumption here, as documented before, is that a higher fraction of remittance-receiving households in the village will play a strong role in migration decision, through stimulating more labor force to migrate. In terms of the receipt of remittances, we also take the fraction of households receiving remittance in the original village excluding household *i* as an instrumental variable to explain the remittance decision. It is more clear that the fraction in a village may have a positive effect on remittance decision. In addition, borrowed from Adams and Cuecucha (2013), a second instrument is the

[19] The existing literature highlights the role that social networks play in migration decision. Zhang and Li (2003) finds that social networks are a key factor in migration decision. And, because of social networks, rural migrants from the same village are more likely to clustered in the same city.

distance to the nearest county times the age of household head. The distance to the nearest county is a proxy for the economic development. Because of poor transport facilities, a village far away from the nearest county seat may be less wealthy, which may increase the probability (the need) for households to receive remittances. The age of household head may also affect the remittance decision, supposing that altruism is the key factor in the remittance decision and elderly household members spend more on medical care.

2.5. Empirical findings

2.5.1. The effect of migration and remittances on school enrollment

Table 2-6 The effects of migration and remittances on Education Decisions

	Probit Model		Probit Model	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
migrant-sending household	-0.091	-0.014		
	（0.0600）	(0.0094)		
Remittance-receiving household			-1.057**	-0.165
			（0.4273）	(0.0668)
Ln(*Remittance*)			0.101**	0.016
			(0.0482)	(0.0075)
Child characteristics	YES	YES	YES	YES
Households characteristics	YES	YES	YES	YES
Household Assets	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Number of Observations	4453		4453	
Mean of dependent variables	88.32%		88.32%	
Pseudo R squared	0.2112		0.2140	

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for child/household characteristics, household assets and provincial dummies.

Source: Child-Level database with children aged between 7 ~18. Author's calculation from 2013 China Household Income Project.

Table 6 displays estimates of the Probit model measuring the effect of migration and remittances on educational decision. When we use "migrant-sending households or not" as the main explanatory variable, the result shows that children in households with migrants are less likely to attend school than those in households without migrants, but not statistically significant. But it provides evidence of a significantly negative correlation between remittance-receiving households and school enrollment, showing that school enrollment is 1.65% lower for children in remittance-receiving households than those in households without remittances. We also include the variable *Ln(Remittances)* in the regression to capture whether the decision to remit and the amount of remittances will differently affect human capital investment. Given the concern that the decision to migrate is always related to the decision(intention) to remit, then it is the case that to improve the welfare of their family, people from less affluent households tend to migrate with the intention of sending remittances back. Seen from the result, after accounting for the remittance decision, the amount of remittances that a household received is associated with higher school enrollment.

It turns out that children in receiving households have different school enrollment preferences than those in non-receiving households, while there is no significant enrollment difference for children in households with or without migrants. However, for migrant-sending households, remittances received or not will also affect the school decision through increasing income and then enhance human capital accumulation. Furthermore, in non-receiving households, those send migrants are potentially endogenous to educational decisions because of the lack of labor supply. Since the role that remittances(migration) plays may be differential in households with migrants (without remittances), we further try to disentangle the effect of remittances from that of migration. Using migrant-sending but non-remittance receiving households as the reference group, it is clear that the coefficients of non-migrant sending and non-remittance receiving households (remittance-receiving households with migrants) can reflect the effects of migration(remittances) on educational decision in non-remittance(migrant-sending) households, as shown in Table 7. The effect of migration in non-receiving households is significantly negative at 10 percent level and the marginal effect reaches 0.024, which indicates that for children in migrant-sending and non-receiving households, the school enrollment is 2.4% less than those in non-migrant sending and non-remittance receiving households. On the other hand, remittances seem to be associated with higher enrollment in migrant-sending households, but not statistically significant. Although the existing literature finds that rural girls are disadvantaged in terms of enrollment and school performance (Connelly and Zheng, 2003), our result shows no gender effects.

Table 2-7 The effect of remittances on Education Decision

	Coefficient	Marginal Effect
Non-migrant non-receiving	0. 156**	0. 024
	(0.069)	(0.0118)
Migrant receiving	0. 020	0. 003
	(0. 0823)	(0. 0126)
Migrant non-receiving	Reference	
Child characteristics	YES	YES
Households characteristics	YES	YES
Household Assets	YES	YES
Provincial dummies	YES	YES
Number of Observations	4425	
Mean of dependent variables	88.23%	
Pseudo R squared	0.2027	

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for child/household characteristics, household assets and provincial dummies.

Source: Child-Level database with children aged between 7 ~18. Author's calculation from 2013 China Household Income Project.

The findings above document the different impacts of migration and remittances on educational decision. Although it shows a decreasing trend on school enrollment for children both in migrant-sending households and remittance-receiving households, the effects of migration and remittances are diverse when taking the three groups into account. The effect of migration is significantly negative in households without remittances. This finding highlights the determinant effect of the absence of parental migrants in the household, children are left-behind with greater labor burdens and less educational assistance, being more likely to work(migrate) rather than to attend school. At the same time, children can benefit for remittances. Remittances can act as an insurance mechanism, which is illustrated by the statistically positive effect of *Ln(Remittance)* on school enrollment.

Furthermore, we use sub-samples of the child-level database, which include children aged between 7~12 (who should be in primary school), children aged between 13~15 (who should attend secondary junior high school) and children aged between 16~18 (who should enroll in senior high school), respectively. Using the same approach, marginal effects are listed in Table 8. Unsurprisingly, the coefficient of remittance-receiving household is only statistically negative in the subgroup with children aged between 16~18, who should enroll in high school which is not compulsory but costly. But it also indicates that on average, a 10 percent increase in the amount of remittances is associated with a 6.3 percent increase in the likelihood of attending senior high school, controlling for the decision to remit and other variables. Also Table 8 provides evidence that in the medium group (13~15), the impact of remittances in households with migration is significant and positive, the school enrollment rate being nearly 6.5% more in households with remittances than those without remittances.

Table 2-8 The effect of migration/remittances on Education Decision-Subgroup

Variable	Children between 7~12 Marginal Effect	Children between 13~15 Marginal Effect	Children between 16~18 Marginal Effect
Migrant-sending	-0.009	-0.004	-0.027
	（0.0090）	(0.0153)	(0.0256)
Remittance-receiving	0.106	-0.140	-0.662***
	(0.0774)	(01157)	(0.1767)
Ln(*Remittance*)	-0.012	0.021	0.063***
	(0.0085)	(0.0135)	(0.0200)
Migrant non-receiving	Reference	Reference	Reference
Non-migrant non-receiving	0.0116	0.034**	0.023
	（0.0113）	(0.0174)	(0.0330)
Migrant receiving	0.004	0.065***	-0.053
	（0.0120）	(0.0208)	(0.0351)
Child characteristics	YES	YES	YES
Household characteristics	YES	YES	YES
Household Assets	YES	YES	YES
Provincial dummies	YES	YES	YES
Number of Observations	2086	1093	1274
Mean of dependent variables	0.9616	0.9378	0.708

Notes: 1) Standard errors in parentheses. 2) *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3)All regressions also include control variables for child/household characteristics, household assets and provincial dummies.

Source: Household-Level database with at least one child at school in 2013. Author's calculation from 2013 China Household Income Project.

2.5.2. The effect of migration and remittances on educational investment

To investigate the impact of migration on educational investment, Table 9 reports the estimation results using the Tobit Model, showing the unconditional marginal effects and the marginal effects conditional on a positive educational investment. The bottom of the table shows the result of the Wald test of the exogeneity of the instrumented variable. The test statistic is significant, which implies that the coefficient in the Tobit model is underestimated and the estimated marginal effects from IV-Tobit are consistent and unbiased. The increase in magnitude in IV-Tobit Model implies that OLS estimates are biased downward by the self-selection of migration decision. One reason may be that households that send migrants with the intention of sending remittances may be less affluent and have to consume more on other resources, such as food or health care.

Table 9 shows that there is a negative association between migration and household spending on education, which is statistically significant. After using instrumental variables, the unconditional marginal effect is -1.673 for all of the households, and the marginal effect for households with positive educational investment is -1.582, indicating that households with migrants spend significantly less on children at school. The possible explanation for the negative impact of migration is that the presence of the migration network represented by migrating household members can facilitate the migration of other household members, which subsequently increase the opportunity cost to educational investment (Hu, 2012).

Table 2-9 The effect of migration on Educational Investment

	Tobit		IV－Tobit	
	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)
Migrant-sending	-0.323***	-0.309***	-1.673***	-1.582***
	（0.0926）	（0.0884）	（0.3370）	（0.3161）
Household characteristics	YES	YES	YES	YES
Household Assets	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Instrument				
Fraction of receiving remittances			YES	YES
Number	3867	3867	3867	3867
Pseudo R squared	0.0285	0.0285		
Wald chi2（1）			17.34	17.34
Prob > chi2			0.000	0.000

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for household characteristics, household assets and provincial dummies.

Source: Household-level database with at least one child at school in 2013. Author's calculation from 2013 China Household Income Project.

What about the role that remittances play in educational investment? Table 10 lists the marginal effects from Tobit and IV-Tobit models for remittance-receiving versus non-receiving households. After correcting the potential bias due to the endogeneity of remittances in Tobit model, we can also see an increase in the marginal effect of the coefficient, indicating that the receipt of remittances is endogenous to educational investment. This may be due to that rural households consider remittances as an explicit way of funding education of their children (Hines, 2015). As reported in Table 10, the coefficient of "receiving remittances" is significantly negative. It should be noted that the negative association between the receipt of remittances and educational expenditures indicates that households with lower expenditure have a greater need for remittances, which means that these households are probably poorer and need the transfer income(remittances) from migrants. In fact, controlling for the receipt of remittances, the coefficient of "*Ln(Remittance)*" is significantly positive, suggesting that when households receive more remittances, they will spend more on education. Another possible explanation for the negative coefficient of the receipt of remittances is that migrants being young labor in the household, the ones left-behind are older people, less educated, and may value less education (Démurger and Wang 2016).

Table 2-10 The effect of remittances on Educational Investment

	Tobit		IV－Tobit	
	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)
Remittance-receiving	-0.383***	-0.366***	-1.200***	-1.142***
	(0.1045)	(0.0997)	(0.2302)	（0.2183）
Household characteristics	YES	YES	YES	YES
Household Assets	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Instruments				
Fraction of receiving remittances			YES	YES
Age*distance			YES	YES
Number of Observations	3867	3867	3867	3867
Pseudo R squared	0.0286	0.0286		
Wald chi2（1）			15.91	15.91
Prob > chi2			0.000	0.000

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for household characteristics, household assets and provincial dummies.

Source: Household-level database with at least one child at school in 2013. Author's calculation from 2013 China Household Income Project.

Consistent with the different effects of migration and remittances on educational decision, the impact of migration on educational investment may also be affected by the educational level of children at school. Since primary and secondary junior high school are free in China, if a household spends more on children at primary school or junior high school, it may indicate a higher concern about the quality of the schooling (i.e. in investing in tutoring). On the other hand, school is not compulsory but costly at senior high school, so if households spend more on children at senior high school or college, it may imply that they care more about higher education and long-run return. Although we cannot get access to different categories of educational expenditure in the CHIP data, the China Family Panel Studies in 2014 can provide us such information. Based on CFPS, we find that although fees paying to school for children in compulsory education is limited, households with children in prime school or secondary school still have to spend much on books or other categories related to education, and expenditure on books, food and transportation accounted for nearly 30 percent of total educational expenditure. Regarding children in high school or college, no doubt that tuition is still the main component of total educational expenditure, accounting for 20 percent. Moreover, since the survey just provided information on total educational expenditure, rather than per child educational spending, we restrict the samples to households with only one child at school (67.53% of our total samples) to estimate the different impacts of migration on educational investment based on different subgroups of households (households with one child at primary school or secondary junior high school and households with one child at senior high school or college).

Table 2-11 The effect of migration on Education Investment-Subgroup Samples (Education group)

	Tobit		IV－Tobit	
	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)
	Compulsory Education			
Migrant-sending household	-0.372**	-0.348**	-2.332***	-2.137***
	（0.1383）	（0.1295）	（0.4712）	（0.4262）
Household characteristics	YES	YES	YES	YES
Household Assets	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Instrument				
Fraction of receiving remittances			YES	YES
Number of Observations	1680	1680	1680	1680
Pseudo R squared	0.0203	0.0203		
Wald chi2（1）			18.77	18.77
Prob > chi2			0.000	0.000
	High School or College			
Migrant-sending household	-0.282	-0.273	-1.297	-1.248
	（0.2190）	（0.2116）	（0.9431）	（0.9038）
Household characteristics	YES	YES	YES	YES
Household Assets	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Instrument				
Fraction of receiving remittances			YES	YES
Number of Observations	841	841	841	841
Pseudo R squared	0.0202	0.0202		
Wald chi2（1）			1.22	1.22
Prob > chi2			0.2689	0.2689

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for household characteristics, household assets and provincial dummies.

Source: Household-level database with only one child at school in 2013.

Table 11 reports the associated unconditional marginal effects and conditional marginal effects on households with positive educational expenditure based on migrant-sending households or not. Wald test show that for households with one child in primary school or junior high school, the marginal effect results from Tobit Model seems to be inconsistent and biased. By contrast, it does not seem to be the same case for households with one child in senior high school or college. Interestingly, households with migrants tend to spend much less on compulsory education, indicating that households without migrants concern more about the quality of compulsory education. On the other hand, for households with one child in senior high school or college, the marginal effects are not significant, indicating that migrant households do not have different investment preferences in higher education.

In addition, the different marginal effects of remittances on educational investment based on different subgroups of households are listed in Table 12. In households with children in primary school or junior high school, the marginal effects from IV-Tobit model shows a significantly negative marginal effect between remittance-receiving households and education expenditure. However, after controlling the remittance decision, an increase in the amount of remittances is correlated with an increase in educational expenditures, implying that in these poorer households, migrants left for explicit purpose of remitting. In households with children at senior high school or college, Tobit result shows that the receipt of remittances does not significantly affect investment on education.

Table 2-12 The effect of remittances on Education Investment-Subgroup Samples (Education group)

	Tobit		IV－Tobit	
	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)	Marginal Effect (Unconditional Expected Value)	Marginal Effect (Conditional on being uncensored)
	Compulsory Education			
Remittance-receiving	-0.707***	-0.662***	-1.702***	-1.586***
	(0.1549)	(0.1450)	(0.3232)	（0.2994）
Household characteristics	YES	YES	YES	YES
Household Asset	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Instruments				
Fraction of receiving remittances	YES	YES	YES	YES
Age*distance	YES	YES	YES	YES
Number of Observations	1680	1680	1680	1680
Pseudo R squared	0.0220	0.0220		
Wald chi2			12.22	12.33
Prob > chi2			0.000	0.000
	High School or College			
Remittance-receiving	-0.023	-0.022	-0.814	-0.786*
	(0.2606)	(0.2519)	(0.5773)	（0.5563）
Household characteristics	YES	YES	YES	YES
Household Asset	YES	YES	YES	YES
Provincial dummies	YES	YES	YES	YES
Instruments				
Fraction of receiving remittances	YES	YES	YES	YES
Age*distance	YES	YES	YES	YES
Number of Observations	841	841	841	841
Pseudo R squared	0.0201	0.0201		
Wald chi2			2.37	2.37
Prob > chi2			0.1237	0.1237

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for household characteristics, household assets and provincial dummies.

Source: 2013 China Household Income Project. Household-level database with only one child at school in 2013.

To sum up, three findings are worth emphasizing. First of all, both households with migrants and households with remittances spend less on education, and the marginal effect of migrant-sending households is much larger than that of remittance-receiving households. Second, focusing on households with one child at school, we find that both households with migrants or remittances tend to spend much less on compulsory education, indicating that households without migrant value more about the quality of compulsory education. Third, it turns out that the receipt of remittances and the amount of remittances relate to household human capital investment in opposite directions. After accounting for the receipt of remittances, the amount of remittances is associated with higher education expenditures. Moreover, it should be noted that the negative relationship between the receipt of remittances and household education expenditures indicates that the motivation of migrating in these households is to send remittances back because of their less affluent income. While in migrant-sending households, since the left-behind are always older and less educated people, they may less value less education.

2.6. Explaining the Low Investment in Education

2.6.1. Marginal Budget Shares

The results above show the negative relationship between migration/remittances decision and investment in education, and that the effect of migration seems to be much larger than that of remittances. It should be noted that different types of households have structural differences in consumption patterns, as shown in Table A3. Unsurprisingly, rural households allocate most on food and closing, which accounts for almost 50% of total budget. In contrast, migrant-sending and remittance-receiving households spend more than their counterparts. Focusing on the comparison of spending on education, we can see that both migrant-sending and remittances-receiving households tend to spend less on education while households without migrants/remittances prefer to spend more. Whereas households send migrants or received remittances spend only 13.73% and 13.21% of their consumption expenses on education, non-migrant sending or non-receiving households spend 14.89% and 14.76% for education, and the gap is significant at 1%. It is reasonable since that the migrant-sending/remittance-receiving households are less wealthy or with more elderly left-behind, thus the households are more likely to spend money on food or medical care rather than education. The similar result is shown for medical care, showing that poorer households (with migrants/remittances) spend more on health care. And this statistic result also indicates that remittances are usually used for consumption rather than human capital investment.

To interpret this differences in consumption pattern, we also to analyze the household marginal educational expenditure, as well as the marginal expenditure pattern of the households. That is, how migration and remittances affect the expenditure pattern at the margin. To solve this question, a Working-Leser Model (Working, 1943; Leser, 1963) is employed, which relates the budget share linearly to the logarithm of total household expenditure. Appendix B adds these details to the analysis.

The objective of this section is to explain the marginal expenditure pattern of the households, especially spending on human capital investment, so we use the household-level database with at least one child at school in 2013. The regression results based on Equation (7) for the five categories of commodities are reported in Table A.4 and A.5 in Appendix. Then, taken these coefficients in the estimated equations, the marginal budget share and the elasticity of specific categories are listed in Table 13. From Table 13, we can see that compared to households without migrants, households with migrants or remittances spend less at the margin on education. Specifically, at the mean, households with migrants spend 3.82% less at the margin on education than households without migrants. On the other hand, it shows that in fact, households with remittances spend 2.65% more at the margin on education than their counterpart, but not statistically significant. Why these household do not prefer to invest more on human capital? It can be explained by the marginal budget shares of other commodities. Households with migrants or remittances spend more at the margin on housing (housing can also be interpreted as another form of investment for rural households) and health care. And as mentioned above, households with migrants or remittances are less affluent and with more elderly people in the household, thus they have to allocate more spending on health care, rather than education. This supports the hypothesis that the decision to migrate in poorer households is simultaneous with the decision to remit, for explicit purpose, such as health care. Moreover, households with migrants/remittances are in favor of investment in assets which may immediately improve their quality of life, such as housing (Démurger and Wang, 2016).

Table 2-13 The marginal budget share and elasticity

	Marginal Budget Share					
	Non Migrant	With Migrant	Percentage Difference, Migrant VS. No Migrant	Non Remittance	With Remittance	Percentage Difference, Remittance VS. No Remittance
Education	0.1868	0.1799	-3.82	0.1846	0.1897	2.65
Food	0.3503	0.3471	-0.93	0.3508	0.3387	-3.55
Durables	0.2294	0.2065	-11.05	0.2304	0.1788	-28.84
Housing	0.1601	0.1739	7.90	0.1612	0.1757	8.25
Health	0.0734	0.0926	20.74	0.0731	0.1171	37.64
	Elasticity					
Education	1.25	1.31		1.25	1.44	
Food	0.81	0.77		0.81	0.73	
Durables	1.38	1.39		1.39	1.29	
Housing	0.83	0.88		0.83	0.90	
Health	1.30	1.43		1.27	1.72	

Source: Household-level database with only one child at school in 2013. Author's calculation from 2013 China Household Income Project.

2.6.2. Lower Returns to Education in rural China

Another explanation for the low investment of migrant-sending and remittance-receiving households in children education may be related to the relatively low returns to education in rural China. And even though nine years of education are stipulated compulsory, the education in China has never been completely free (Hu, 2012). Educational expenses such as books and educational supplies still cost a lot for rural households, especially poorer households. Moreover, although more schooling may ease children finding better jobs in the future, rural areas are always characterized by limited education opportunities of lower quality (Hannum and Park, 2009), and the returns to schooling are relatively lower.

Based on China Household Nutrition Survey, Deng and Ding (2013) find that returns to schooling in rural China have increased from 4.02% in 1988 to 8.2% in 2005. Regarding the difference in returns between urban and rural areas, although there are some statistic differences in the returns to education based on difference sources of data, returns to schooling in rural China are still much lower. Li and Li (1994) report that the difference in returns between urban and rural areas is 2 percent in 1988, and then the gap reaches up to 7 percent in 2001 (Li and Ding 2003), decreasing to 2 percent in 2009 (Deng and Ding 2013). Consequently, the lower returns to education in rural China may also be responsible for the lower investment in education.

On the other hand, since the presence of the migration network in urban areas represented by migrating household members can facilitate the migration of other household members, which subsequently increase the opportunity cost to educational investment in rural China. In fact, because of lower quality and lower returns, households with migrants or remittances may value education as a consumption good, rather than an investment good.

2.7. Conclusion

This paper aims at investigating the effect of migration and remittances on school enrollment and educational investment in rural China. Using rural household data from the China Household Income Project 2013, we find that both migration and remittances act as a negative role in educational decision. And when take the age groups of children into account, the effect of remittances is significantly negative and large in older age group. This finding highlights the determinant adverse effect of the absence of parental migrants in the household. But since the amount of remittances is associated with higher enrollment, thus remittances can act as an insurance mechanism. Moreover, we also provide evidence that both migration and remittance decisions adversely affect educational investment, and households with migrants or remittances tend to spend much less on compulsory education. One explanation is that the decision to migrate in less affluent households is always simultaneous with the decision to remit, for explicit purpose, such as health care. Meanwhile, migrant-sending/ remittance-receiving households are in favor of investment in assets which may immediately improve their quality of life, such as housing. The other reason may be related to the lower quality and returns to education in rural China, thus households may view educational investment as a consumption good.

Given the importance of human capital investment in the labor market and the inevitable increase of rural to urban migration, it is worth noting that policy makers should take some action to improve the educational investment in rural areas, especially for poorer households. Some compensatory measures such as Minimum Living Standard Guarantee Program should target these households and improve their poverty situation and the absence of parents. Meanwhile, education officials should hire more qualified teachers to improve the quality of education in rural China. Ultimately, since the institution segmentation is the main factor causing this problem, the negative effect would be ameliorated if the children of migrants can get access to urban schools equally as urban children.

To the end, I also consider these questions for future research. Our findings are limited to our data. Since our result is based on cross-sectional data in 2013, we cannot analyze the time-varying effect of migration/remittances. And the effect of return migrants need to be studied in the future.

3. Wealth effects on consumption in China, 2002-2013

3.1. Introduction

The beginning of the 2000s has witnessed a dramatic increase in Chinese household wealth as well as substantial changes in the components of wealth. Estimates by Li and Wan (2015) show that the level of wealth in 2010 was four times that of 2002. In 2003, estimates from the National Bureau of Statistics[20] indicated that housing was becoming a major component of household wealth, accounting for as much as 47.9% of overall wealth. Using CHIP data 2002 and 2013, Knight et al. (2016) confirm the dominant role of real estate in overall household wealth, and show that the proportion of net housing to overall household wealth has increased from 52.8% to 72.5% at the national level during this period.

The accumulation of household wealth has two main sources: savings from current income and changes in assets valuation (Paiella, 2007). In China, these two sources may act together because in the past decades, Chinese households have experienced large increase in income as well as unprecedented changes in assets prices, notably in real estate prices.

[20] This early survey by the National Bureau of Statistics (NBS) covers 3,997 households in cities in Tianjin municipality and Hebei, Shandong, Jiangsu, Guangdong, Sichuan, Gansu and Liaoning provinces between May and July 2002.

Before the implementation of economic reforms at the end of the 1970s, Chinese households owned little private property. When the government ended up the single public ownership structure and started to protect private property rights, the amount of saving deposits increased rapidly. In 1978, the total amount of savings was only 21.1 billion Yuan and per capita savings was only 219 Yuan. By 2014, the amount of savings had reached 48,526.1 billion Yuan and per capita savings now amount to 35,477 Yuan, which is nearly 161 times the level in 1978.

Besides financial assets, housing assets have also increased dramatically in the last two decades, and this increase is mainly due to the surge in housing prices, notably after 2003. From the end of the 1990s, China started to reform the housing system, allowing and protecting private housing (Sato *et al.,* 2013). Since then, the real estate industry has developed rapidly and has in turn stimulated more and more residents to invest in real estate. Consequently, the market value of housing has risen continuously. As documented by Li and Wu (2014), the national average housing price more than doubled from 2000 to 2010, and for Beijing only, residential housing price surged from 4,557 to 17,151 yuan per square meter within these ten years.

In this chapter, we assess the strength of the correlation between household wealth and consumption. Given the above mentioned changes in the 2000s, assessing the importance of the wealth effect on household consumption is meaningful. It is also relevant in terms of macroeconomic policy when prices are subject to potentially large fluctuations. We address the following research questions: What is the effect of wealth on consumption in China and is there any change between 2002 and 2013? What are the differential effects on consumption associated with household wealth between urban and rural China? How do consumption and consumption patterns response to the changes in the market value of housing and financial assets? Is the wealth effect heterogeneous across households?

We begin the chapter with a review of relevant empirical literature on the wealth effect. We then describe and discuss the data we use to assess this effect in China. The next section puts forward our research methodology. Finally, we present estimates of the wealth effect measured separately for urban and rural households as well as over time. We highlight the differentiated impact of financial wealth and housing wealth on household consumption and provide evidence of heterogeneity across different groups of households.

3.2. Measuring the wealth effect: a review of the evidence

3.2.1. Theoretical evidence

Studies focusing on the link between wealth and consumer spending mainly rely on the life cycle model, which states that over the life cycle, people first accumulate and then deplete their wealth assets in order to smooth out their consumption. The existing literature based on the life-cycle hypothesis generally finds that consumption depends on permanent income, household wealth, time preference and other demographic characteristics.

The available literature also argues that consumption may respond differently to different components of wealth. In particular, it emphasizes the differential effects of financial and housing wealth, because these components are different in terms of liquidity, measurability and capital gain. As a matter of fact, several reasons are held to interpret their differential effects. First, households may consider that some forms of wealth are less liquid and more volatile than others. For instance, Pichette and Tremblay (2003) suggest that changes in housing market are less volatile than shocks to financial market, and that the transaction costs of housing wealth are much higher than that of financial assets. Consequently, households may view increases in housing wealth as more certain or more permanent (Case et al. 2005), and they might adjust their consumption decision more rapidly to changes in housing wealth. In that case, the housing wealth effect might be larger than the financial wealth effect.

Second, households may perceive some components of wealth more difficult to measure than others or less tractable. Because houses are less homogenous and less liquid, consumers may find it hard to measure the present value of the housing wealth they hold, resulting in a housing wealth effect smaller than the financial wealth effect. On the other hand, Dvornak and Kohler (2003) point out that before retirement, households might not be aware of the value of some indirect financial holdings, such as pension or other subsidies.

Third, households "hold" different assets classes in separate "mental accounts" (Thaler 1990), leading them to respond differently to changes in their gross or net positions in financial or housing wealth. For instance, if capital gains are unanticipated and are viewed as windfall, they might be treated as an increase in wealth. By contrast, small gains, such as small changes in cash, could be viewed as income, and spent.

Fourth, housing assets may serve more than one purpose because housing is not only an asset but also an important consumption good (Juster et al. 2006). Young homeowner may benefit from increasing housing price, but in the meantime, they are also exposed to house price uncertainties. If they expect to buy a larger house in the future as their family grows, then the increasing house price might not lead to welfare improvement, resulting in a lower marginal propensity out of consume from housing wealth.

Fifth, housing may provide consumption insurance, and therefore affect consumption patterns differently than financial wealth does. In this case, the housing wealth might be expected to be larger than the financial wealth effect.

3.2.2. Empirical evidence

Traditional macroeconomic estimates investigate the size and significance of the impact of changes in wealth on consumption, and suggest a positive correlation between wealth and consumer spending. Yet, as far as wealth components are concerned, there is no strong consensus regarding whether one type of wealth effect dominates. Hence, while Dvornak and Kohler (2007) find a marginal propensity to consume out of stock market wealth larger than that with respect to housing wealth in Australia, Benjamin et al. (2004) and Case et al. (2005) report a housing wealth effect upon consumption substantially larger than the financial wealth effect in the US.

More recently, a host of literature has focused on estimating the wealth effect with household level datasets in order to account for household-level demographic and economic characteristics that may lead to heterogeneity in preferences. Also, studies relying on aggregate data cannot identify whether increases in consumption are effectively observed for households experiencing an increase in wealth (Bostic *et al.*, 2009).

Using UK micro data, Campbell and Cocco (2007) investigate how household consumption varies with housing prices. They find that the housing wealth elasticity is much larger for older homeowners and smaller for younger renters. Sierminska and Takhtamanova (2007) compare the effect of financial wealth and housing wealth in Canada, Italy and Finland, and report that the effect of housing wealth is much stronger than that of financial assets for the three countries. Corroborating Campbell and Cocco's finding on the UK, they also find that the housing wealth elasticity is larger for older households. Bostic *et al.* (2009) provide evidence of a relatively large housing wealth effect in the case of the U.S., showing that the housing wealth elasticity is estimated in the range of 0.06 over the 1989-2001 period among homeowners, while the estimated elasticity of consumption with respect to financial wealth is in the range of 0.02.

A number of studies also investigate the heterogeneity in the wealth effect across the age distribution. Using microeconomic data on the US, Lehnert (2004) estimates consumption elasticities from housing wealth by age quintile and finds that the youngest group has a higher elasticity of consumption than the next two age quintiles. He also shows that households on the verge of retirement have large housing wealth effects too, and interpret this result as those households being the likeliest to "downsize" their house and thus realize any capital gains. In a similar vein, Bover (2005) shows that the effect of housing wealth is the largest for Spanish prime age households aged between 35 and 44 and decreases afterwards. Using the China Health and Retirement Longitudinal Study, Xie (2012) finds that in urban China, the response of household consumption to housing wealth is much larger for younger families than that for older families. By contrast, Bostic *et al.* (2009) find damped wealth elasticities and elevated income elasticities among households aged 25-35, relative to older age cohorts. These findings are consistent with the lifecycle hypothesis, which states that income elasticities decline whereas wealth elasticities increase during the peak earnings years. Sierminska and Takhtamanova (2007) also find a significantly lower housing wealth effect for younger households in Canada, together with a higher income effect.

3.3. Data: Definitions and stylized facts

3.3.1. Data definitions

For the analysis of the wealth effect, we use data from the 2002 and 2013 China Household Income Project (CHIP) urban and rural surveys. The CHIP2002 survey was conducted in 20 provinces and 2 province-level municipalities in China, covering 9,200 rural households and 6,835 urban households. The CHIP2013 data cover 12 provinces and 2 province-level municipalities in China, with approximately 10,000 rural households and 6,674 urban households. The 2002 survey is described in Li et al. (2008), and Appendix A.5 of this volume provides details on the 2013 survey.

All the households surveyed were drawn from the sampling framework of the regular household survey annually conducted by the National Bureau of Statistics (NBS) of China (Luo and Li, 2016). The field survey includes detailed information about the demographic characteristics, household structure, household assets and employment, while the information about items of income and expenditure is provided directly from the NBS regular survey. For each dataset (urban and rural, 2002 and 2013), we exclude the top 0.5 percent of household consumption, total income, net wealth and seven wealth components as outliers. The sample size is then 6,747 urban households and 8,945 rural households in 2002, and 10,037 rural households and 5,948 urban households in 2013.

The dataset provides detailed information on household-level consumption-related expenses and on family's wealth. For the purpose of this analysis, we focus alternatively on total household consumption expenditure[21], as well as on food (and clothing) *versus* non-food consumption expenditures. Non-food consumption expenditure includes spending on durable goods[22], on communication and transportation[23], on housing, on education[24], on health care[25], and on other goods and services[26]. Household wealth includes the following seven components: 1) land[27], 2) financial assets, 3) net housing value[28], 4) durable assets, 5) productive fixed assets, 6) other assets[29], and 7) non-housing debt (Knight *et al.*, 2016; Li and

[21] The data also include expenditures for household business and other expenditures (such as taxes and fees, expenses on properties and transfers, etc.). For the purpose of this analysis, we focus only on consumption expenditure.

[22] There is a discrepancy between the 2002 and the 2013 surveys for the definition of this category. CHIP2002 includes expenditure on durable goods only, while CHIP2013 includes expenditure on durable goods and also consumption on miscellaneous items, such as dishes or tea sets.

[23] This category includes purchase of vehicles, expenses on fuel and public transportation, as well as communication costs.

[24] Spending on education includes spending on education, entertainment, and cultural activities.

[25] Health consumption refers to spending on medicines, medical equipment and hospital bills.

[26] Other consumption includes purchase of other items, like jewelry, cosmetics, hotel accommodation, haircuts, etc.

[27] In urban areas, land asset is set to be zero.

[28] Net housing wealth refers to the net value of the household's home for homeowners. For real estate rented or provided for free by the work unit or by relatives, the net housing wealth is set to zero (Li and Wan, 2015). Housing purchasing (construction) loan debt or borrowing from others is deducted when calculating the net value of housing. For owners of multiple estates, the total net housing wealth is used.

[29] 'Other assets' refers to the present value of various assets, resources, claims and other rights (including collectibles, antiques, not reclaimed debts and paintings). For rural households, 'other assets' is set to be zero.

Wan, 2015). Financial wealth is calculated as the sum of bank deposits, securities and stocks, lending money, borrowings and cash in hand. In principle, it should be strictly positive for all households. Yet, a number of households in the dataset failed to report the exact value of their financial wealth or reported no financial asset at all. Assuming that these households should have non-zero financial assets, we predict their financial assets based on the following function (Meng, 2007)[30]:

$$logFinance = \beta_0 + \beta_1 Head + \beta_2 Labor + \beta_3 Prov + \mu \tag{1}$$

where *Finance* refers to household financial wealth. *Head* is a vector of household head information including age, age square and years of schooling (of the household head and his/her spouse). *Labor* measures the number of working adults in the household. *Prov* stands for provincial dummies. Regression results based on Equation (1) are reported in Table A.1 in Appendix.

Wealth, consumption and income data are adjusted for price differences over time and over space, using Brandt and Holz (2006) provincial-level spatial price deflators updated to 2013. CPI index is used to deflate the wealth distribution over the period, and household weights are used in order to make data nationally representative.

[30] The number of households for whom financial assets are replaced by predicted value is 457 and 247 for urban and rural households in 2002, and 138 and 243 for urban and rural households in 2013, respectively.

3.3.2. Stylized facts on household wealth and consumption

Table 1 lists household net wealth and wealth components for the years 2002 and 2013, in both rural and urban areas. It first shows that household net wealth has dramatically increased from 2002 to 2013, in both rural and urban areas. In 2013, the overall net wealth reached 590,000 yuan in urban areas, at an annual growth rate of 13.5 percent, three points larger that the rural counterpart. Similarly, the per capita household net wealth reached peaks in 2013, 4.5 times higher in urban areas than in 2002, and 3.5 times higher in rural areas than in 2002. Regarding the components of household wealth, they all grew during this period, in both rural and urban areas, but at a different pace. The market value of housing experienced the largest increase, with a rapid annual growth rate of 18 percent and 16 percent for the urban and the rural samples, respectively. By contrast, household financial wealth increased at sharply contrasted rates for urban and rural households: the annual growth rate did not reach 5 percent per year for urban households while it peaked 14 percent per year for rural households. Finally, the non-uniform evolution of household wealth between rural and urban households resulted in a growing household wealth disparity between rural and urban areas. While, the household net wealth per capita level was only 2.82 times higher in urban areas than in rural areas in 2002, the gap reached 3.6 times in 2013. This finding corroborates recent estimates that show that the national Gini coefficient of wealth distribution increased significantly from0.494 in 2002 to 0.617 in 2013 (Knight *et al.*, 2016).

Table 3-1 Household net wealth

	2002	2013	Yearly real growth rate during 2002-2013
Urban (yuan)			
Household net wealth	142,070	590,552	13.83%
Household net wealth per capita	50,778	226,463	14.56%
Household financial assets per capita	16,648	27,665	4.73%
Household net housing assets per capita	29,556	182,905	18.02%
Household other assets per capita	4,574	15,894	11.99%
Observations	6,747	5,948	
Rural (yuan)			
Household net wealth	69,016	204,570	10.38%
Household net wealth per capita	17,975	62,931	12.07%
Household financial assets per capita	2,640	11,261	14.10%
Household net housing assets per capita	7,259	37,942	16.22%
Household other assets per capita	8,077	13,729	4.94%
Observations	8,945	10,037	

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: 1) This table uses CPI index to adjust the wealth level in 2002 to real terms. PPP index and weight are used when calculating household wealth. 2) For each dataset, the top 0.5 percent of household consumption, total income, net wealth and seven wealth components are excluded as outliers. 3) For households who failed to report the exact value of their financial wealth or reported no financial asset at all, the predicted financial assets are used instead.

Table 2 displays wealth components shares and their change from 2002 to 2013. Several findings stand out. First, the net housing assets are the main component of household net wealth, in both urban and rural areas. The net housing wealth accounted for respectively 38 and 49.5 percent of total net wealth for rural and urban households in 2002, and these shares have sharply increased, up to 62 and 68 percent in 2013.[31] As housing prices have soared

[31] Using a panel micro survey data in 2010 and 2012, Xie and Jin (2014) also show that net housing is the main component of the household wealth, as it accounts for as much as 80% of the overall net wealth in 2012.

during this period[32], housing not surprisingly appears as the largest contributing factor to the increase of net wealth. In contrast, household financial assets saw their share in total net wealth dropping sharply for urban households (from 38 to 20 percent), while remaining stable for rural households.

Table 3-2 Household wealth structure

Shares (%)	Urban		Rural	
	2002	2013	2002	2013
Land assets	-	-	34.72	16.06
Financial assets	37.95	19.84	12.89	12.04
Housing assets	49.55	68.19	37.93	61.93
Durable assets	11.08	9.22	8.15	6.42
Productive fixed assets	0.98	1.25	8.66	4.14
Other assets	1.84	1.75	-	-
Non housing debt	-1.40	-0.25	-2.34	-0.59
Total assets	100	100	100	100

Source: Author's calculation from CHIP 2002 and CHIP 2013.

Note: See Table 1. The wealth structure is calculated using weights.

Table 3 provides a comparison of household total consumption, food consumption and non-food consumption for the years 2002 and 2013. Consistent with the rapid increase in household wealth, household consumption also experienced an increase during this period. In 2013, urban household total consumption per capita reached 19,500 yuan, almost 2.5 times that of 2002. Rural household consumption per capita experienced an even larger increase, with an annual growth rate above 12 percent. As far as consumption components are concerned, non-food consumption saw the largest increase during this period, with an annual

[32] See Knight *et al.* (2016) for details.

growth rate close to 10 percent for urban households and at 13.6 percent for rural households. In comparison, food consumption grew at only 5.7 percent per year for urban households and 7.8 percent for rural households.

Table 3-3 Household Consumption

	2002	2013	Yearly real growth rate during 2002-2013
Urban (yuan)			
Total consumption expenditure	22,554	52,311	7.95
Total consumption per capita	7,926	19,513	8.54
Expenditure on food	11,040	20,260	5.67
Expenditure on non-food	11,515	32,051	9.75
Rural (yuan)			
Total consumption expenditure	8,396	25,865	10.77
Total consumption per capita	2,154	7,685	12.26
Expenditure on food	4,651	10,600	7.78
Expenditure on non-food	3,745	15,265	13.63

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: "Expenditure in non-food" includes all consumption expenditure except food and clothing. This table uses CPI index to adjust the consumption level in 2002 to real terms. PPP index and weight are used when calculating household consumption.

3.4. Empirical specification

To estimate how consumer spending responds to household wealth, we employ the standard approach that relates household consumption to wealth in a reduced-form model, controlling for income and socioeconomic characteristics (Dynan and Maki, 2001; Lehnert, 2004; Bostic *et al.*, 2009):

$$logC = \beta_0 + \beta_1 logY + \beta_2 logW + \beta_3 X + \beta_4 Prov + \mu \qquad (2)$$

where C stands for consumption, Y is current income, and W is the value of household net wealth. The vector X includes both information on household head (age, age square and education) and household characteristics (household size). *Prov* stands for provincial dummies to account for unobservable variables that can affect household consumption at the provincial level. Apart from focusing on the effect of net wealth, we also estimate how consumption responds to household gross wealth (measured by excluding household debt).

Moreover, because households may respond differently in terms of consumption to various components of wealth, we also estimate a modified version of equation (2) that distinguishes financial, housing and other forms of wealth:

$$logC = \beta_0 + \beta_1 logY + \beta_2 logW^F + \beta_3 logW^H + \beta_4 logW^O + \beta_5 X + \beta_6 Prov + \mu \qquad (3)$$

where W^F is household financial asset value, W^H is the net value of real estate, and W^O is the value of other assets a household holds.

For all the sub-samples, we exclude households reporting non-positive consumption. Moreover, since the logarithm of wealth values is used as the main independent variable, we also exclude households with non-positive net wealth, non-positive net housing values or non-positive financial asset. In this case, we focus on homeowners only. Table A.6 in Appendix displays summary statistics for the dependent and the independent variables.

Then, we expand the standard approach in two ways. First, we pool the two cross-sectional datasets in order to test whether the estimated wealth elasticities significantly vary over time and between rural and urban areas. The pooled model is given by:

$$logC = \beta_0 + \beta_1 logY + \beta_2 logW * D + \beta_3 D + \beta_4 X + \beta_5 Prov + \mu \qquad (4)$$

where *D* is either a year dummy or an urban area dummy, and *W*D* is the year-specific (urban-specific) household net wealth term. Using the same functional form, we also estimate the year-specific (urban-specific) financial and housing wealth effects.

As mentioned above, the existing literature provides evidence that the coefficient of wealth varies with household age, household income and wealth classes[33]. In order to investigate the heterogeneity in wealth effect along various household characteristics, we introduce separate interaction terms between the wealth variable(s) and the age of the household head, income quintiles and wealth quintiles.

3.5. The total wealth effect on household consumption

Table 4 shows how consumption responds to household net wealth in the years 2002 and 2013, and in rural and urban areas separately. As a starting point, and not surprisingly, the estimated elasticity of consumption to net wealth is highly significant for both years and for both urban and rural households. A comparison of the estimates across years shows that the estimated elasticity of consumption to household net wealth increases for both urban and rural households, suggesting an increase in the importance of household net wealth to consumption over the two years. Among urban households, we find that the net wealth elasticity estimates range from 0.072 in 2002 to 0.199 in 2013. In rural areas, the estimated elasticity of consumption with respect to net wealth increases from 0.106 to 0.232 over the

[33] See Section2. Farinha (2008) also finds that the wealth effect varies with age, income and wealth classes in Portugal.

two years. Table 7 confirms that the increase of the wealth effect is significant for both urban and rural households. In contrast to the increasing wealth effect, the income effect is found to decline over time, even though the elasticity of consumption with respect to income remains much larger than that with respect to wealth. The income effect dropped by 20 percent between 2002 and 2013 for urban households and by 9.5 percent for rural households.

Table 3-4 The estimated net wealth elasticity, 2002-2013

	2002 urban	2013 urban	2002 rural	2013 rural
Log net wealth	0.072***	0.199***	0.106***	0.232***
	(0.0090)	(0.0089)	(0.0097)	(0.0069)
Log income	0.635***	0.504***	0.358***	0.324***
	(0.0119)	(0.0122)	(0.0099)	(0.0075)
Household size	0.039***	0.027***	0.066***	0.062***
	(0.0066)	(0.0054)	(0.0040)	(0.0034)
Age of household head	0.001	-0.003	0.019***	-0.003
	(0.0033)	(0.0030)	(0.0034)	(0.0028)
Age square	-0.000	0.000	-0.000***	-0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education of household head	0.008***	0.016***	0.012***	0.009***
	(0.0018)	(0.0019)	(0.0020)	(0.0018)
Provincial dummies	Yes	Yes	Yes	Yes
Observations	4,672	4,647	8,736	9,231
adj. R2	0.563	0.623	0.399	0.524

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: Estimations are done on a sample that excludes households reporting non-positive consumption and households with non-positive net wealth, non-positive net housing values or non-positive financial asset.

Standard errors in parentheses. * *p* 0.05, ** *p* 0.01, *** *p* 0.001.

Tables 4 and 6 further show that the wealth effect in rural areas is larger in magnitude than that of urban areas, in 2002 as well as in 2013. Interestingly, wealth seems to play a more important role in consumption for rural households while for urban households, the effect of household income on consumption is significantly larger. In the short run, urban households are highly sensitive to current income (with an elasticity above 0.5 over the two years) and in turn, they appear less sensitive to wealth in the determination of their consumption. For urban households, the effect of wealth on consumption relative to the income effect increased from 0.11 to 0.39 between 2002 and 2013, while the same increased markedly from 0.30 to 0.72 for rural households. This suggests that wealth is becoming almost as important as income in rural areas, whereas for urban households, the effect of wealth is still much smaller than that of income.

Table 5 presents estimates using gross wealth instead of net wealth as our variable of interest. Findings are very similar: the gross wealth elasticity is significant; it is increasing over time and it is generally larger for rural households than for urban households. Of all the other control variables, as would be expected, we observe a positive relationship between both the household size and the level of education of the household head and household consumption. We also capture a life-cycle effect between the age of the household head and household consumption for rural households in 2002.

Table 3-5 The estimated gross wealth elasticity, 2002-2013

	2002 urban	2013 urban	2002 rural	2013 rural
Log gross wealth	0.074***	0.203***	0.128***	0.243***
	(0.0092)	(0.0087)	(0.0099)	(0.0070)
Log income	0.633***	0.500***	0.347***	0.320***
	(0.0119)	(0.0121)	(0.0099)	(0.0075)
Household size	0.039***	0.025***	0.065***	0.060***
	(0.0066)	(0.0054)	(0.0040)	(0.0034)
Age of household head	0.001	-0.003	0.018***	-0.003
	(0.0033)	(0.0030)	(0.0033)	(0.0028)
Age square	-0.000	0.000	-0.000***	-0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education of household head	0.008***	0.015***	0.012***	0.009***
	(0.0018)	(0.0019)	(0.0020)	(0.0018)
Provincial dummies	Yes	Yes	Yes	Yes
Observations	4,672	4,647	8,736	9,231
adj. R2	0.563	0.626	0.402	0.528

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: See Table 3-4.

Table 3-6 Net Wealth /Housing effect on consumption - By region

	2002		2013	
Log net wealth	0.112***		0.236***	
	(0.0090)		(0.0065)	
Net Wealth*Urban	-0.037**		-0.041***	
	(0.0138)		0.236***	
Log net housing wealth		0.094***		0.171***
		(0.0051)		(0.0044)
Log financial wealth		-0.031***		0.008*
		(0.0033)		(0.0034)
Log other wealth		0.012		0.018***
		(0.0068)		(0.0042)
Net housing*Urban		-0.058***		-0.041***
		(0.0083)		(0.0085)
Finance*Urban		0.043***		-0.001
		(0.0069)		(0.0061)
Other Wealth*Urban		0.017		0.034***
		(0.0096)		(0.0067)
Log income	0.258***	0.215***	0.166***	0.129***
	(0.0160)	(0.0161)	(0.0144)	(0.0148)
Log income*Urban	-1.327***	-1.266***	-1.117***	-1.081***
	(0.1578)	(0.1485)	(0.1379)	(0.1340)
Urban	0.060***	0.055***	0.053***	0.055***
	(0.0034)	(0.0034)	(0.0029)	(0.0029)
Household size	0.012***	0.011***	-0.003	-0.002
	(0.0024)	(0.0024)	(0.0021)	(0.0021)
Age of household head	-0.000***	-0.000***	-0.000	-0.000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Age square	0.011***	0.010***	0.013***	0.013***
	(0.0014)	(0.0014)	(0.0013)	(0.0013)
Education of household head	0.258***	0.215***	0.166***	0.129***
	(0.0160)	(0.0161)	(0.0144)	(0.0148)
Provincial dummies	Yes	Yes	Yes	Yes
Observations	13,408	13,408	13,878	13,878
adj. R2	0.687	0.692	0.664	0.670

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: See Table 3-4.

3.6. Financial and housing wealth effects on household consumption

Table 8 shows estimates for financial wealth and housing wealth elasticities. Our findings conform to those of the existing literature on the importance of home equity for household consumption. Given the unprecedented increase in housing prices, housing assets are unsurprisingly becoming a more important determinant of household consumption. As a result, the effect of the housing value on household consumption increases. Among urban households, the net housing elasticity amounts to 0.032 in 2002, and it increases to 0.124 in 2013. It is significantly higher for rural households (see Table 6) and it has almost doubled in ten years, from 0.088 in 2002 to 0.169 in 2013.

Table 3-7 Net Wealth/Housing effect on consumption - By year

	Urban		Rural	
Log wealth	0.080***		0.099***	
	(0.0091)		(0.0095)	
Net Wealth*Year	0.119***		0.137***	
	(0.0119)		(0.0117)	
Log net housing wealth		0.035***		0.094***
		(0.0058)		(0.0054)
Log financial wealth		0.016**		-0.032***
		(0.0053)		(0.0035)
Log other wealth		0.030***		-0.004
		(0.0060)		(0.0072)
Net housing*Year		0.091***		0.077***
		(0.0086)		(0.0071)
Finance*Year		-0.012		0.041***
		(0.0070)		(0.0050)
Other Wealth*Year		0.033***		0.017*
		(0.0076)		(0.0084)
Log income	0.635***	0.632***	0.379***	0.422***
	(0.0117)	(0.0120)	(0.0097)	(0.0095)
Log income*Year	-0.116***	-0.118***	-0.050***	-0.064***
	(0.0160)	(0.0165)	(0.0121)	(0.0119)
Year	-0.027*	-0.007	-0.038***	-0.008
	(0.0137)	(0.0132)	(0.0111)	(0.0104)
Household size	0.031***	0.026***	0.060***	0.060***
	(0.0041)	(0.0042)	(0.0026)	(0.0026)
Age of household head	-0.001	-0.002	0.010***	0.010***
	(0.0022)	(0.0022)	(0.0020)	(0.0020)
Age square	-0.000	-0.000	-0.000***	-0.000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education of household head	0.011***	0.011***	0.010***	0.010***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Provincial dummies	Yes	Yes	Yes	Yes
Observations	9,319	9,319	17,967	17,967
adj. R2	0.733	0.735	0.703	0.711

Source: Author’s calculation from CHIP 2002 and CHIP 2013

Note: See Table 3-4.

Table 3-8 The estimated housing and financial asset elasticity, 2002-2013

	2002 urban	2013 urban	2002 rural	2013 rural
Log net housing	0.032***	0.124***	0.088***	0.169***
	(0.0058)	(0.0071)	(0.0055)	(0.0046)
Log financial wealth	0.014**	0.004	-0.027***	0.006
	(0.0052)	(0.0047)	(0.0036)	(0.0035)
Log other wealth	0.031***	0.063***	0.008	0.018***
	(0.0058)	(0.0050)	(0.0075)	(0.0044)
Log income	0.631***	0.500***	0.400***	0.351***
	(0.0121)	(0.0125)	(0.0098)	(0.0074)
Household size	0.038***	0.020***	0.062***	0.066***
	(0.0066)	(0.0055)	(0.0041)	(0.0034)
Age of household head	0.002	-0.003	0.017***	-0.001
	(0.0033)	(0.0030)	(0.0033)	(0.0028)
Age square	-0.000	0.000	-0.000***	-0.000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education of household head	0.008***	0.016***	0.012***	0.010***
	(0.0018)	(0.0019)	(0.0020)	(0.0018)
Provincial dummies	Yes	Yes	Yes	Yes
N	4,672	4,647	8,736	9,231
adj. R2	0.564	0.625	0.410	0.535

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: See Table 4.

By contrast, the estimated elasticity of consumption with respect to financial assets is much smaller in magnitude than that of housing wealth, and not significant in the year 2013. Why is the impact of financial assets so elusive? One possible explanation could be that financial wealth is highly correlated with current income, which makes it difficult to clearly identify their respective impact on consumption. Table 6 confirms that the estimated elasticity of consumption with respect to financial wealth is much larger in 2002 for urban households than for rural households. Yet, our estimates from Table 6 and Table 7 suggest that the financial wealth effect almost vanishes over time (down to an elasticity of about 0.01 for both urban and rural households), suggesting a decline in the importance of financial wealth to consumption spending over the decade.

3.7. Heterogeneous wealth effects across household groups

To further investigate the relationship between the age of the household head and the wealth effect, Table 9 reports estimates of a specification that allows the net wealth effect to vary across age groups. First, it indicates that wealth matters for household consumption in all age classes. Second, the profiles of both the net wealth and the housing equity elasticities do not look monotonic, with peaks for prime age households (aged between 40 and 50), and well as for older households (above 60). One possible reason to interpret this result is the negative correlation between wealth accumulation and the need for (precautionary) saving, as documented in the earlier literature (Bover 2006; Farinha 2008). Younger households have larger needs for precautionary saving (because of their higher housing debts or to purchase a larger house in the future as their family grows), which motivates them to vary less their household consumption in response to an increase in housing wealth. In contrast, an increase in the value of their homes for prime age households may reduce the need for other precautionary savings when their consumption is the largest. For older households, because of their smallest need for precautionary saving and their short life expected horizon, they would like to capture the housing wealth gains and vary their consumption decision along with an increase in wealth.

Table 3-9 Net Wealth/Housing effect on consumption - By age group

	2002 urban	2013 urban	2002 rural	2013 rural
Net wealth*Age 20-30	0.075***	0.194***	0.109***	0.224***
	(0.0101)	(0.0103)	(0.0105)	(0.0086)
Net wealth*Age 30-40	0.073***	0.195***	0.110***	0.227***
	(0.0093)	(0.0093)	(0.0098)	(0.0074)
Net wealth*Age 40-50	0.072***	0.199***	0.109***	0.235***
	(0.0091)	(0.0090)	(0.0097)	(0.0070)
Net wealth*Age 50-60	0.070***	0.197***	0.101***	0.232***
	(0.0091)	(0.0090)	(0.0097)	(0.0069)
Net wealth*Age 60-70	0.072***	0.201***	0.100***	0.231***
	(0.0095)	(0.0091)	(0.0102)	(0.0070)
Net wealth*Age >70	0.072***	0.196***	0.114***	0.233***
	(0.0104)	(0.0096)	(0.0121)	(0.0076)
	2002 urban	**2013 urban**	**2002 rural**	**2013 rural**
Net Housing*Age 20-30	0.035***	0.119***	0.090***	0.161***
	(0.0073)	(0.0088)	(0.0070)	(0.0070)
Net Housing*Age 30-40	0.033***	0.121***	0.091***	0.164***
	(0.0061)	(0.0076)	(0.0058)	(0.0054)
Net Housing*Age 40-50	0.032***	0.125***	0.090***	0.172***
	(0.0058)	(0.0072)	(0.0056)	(0.0048)
Net Housing*Age 50-60	0.030***	0.123***	0.082***	0.168***
	(0.0059)	(0.0072)	(0.0056)	(0.0047)
Net Housing*Age 60-70	0.032***	0.127***	0.081***	0.166***
	(0.0065)	(0.0073)	(0.0065)	(0.0048)
Net Housing*Age >70	0.031***	0.122***	0.095***	0.167***
	(0.0078)	(0.0080)	(0.0095)	(0.0057)

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: See Table 4. All regressions also include control variables for household income, family size, age of household head, educational level of household head and provincial dummies.

Finally, Table 10 and Table 11 uncover variations in the effect of wealth depending on the income and the wealth class of the household. First, they show that for both rural and urban areas, the effect of wealth on consumption increases along with the increase of income/wealth quintile, for both 2002 and 2013. Second, a similar pattern also arises showing that the coefficients of net housing wealth vary with the income/wealth class of the household.

Table 3-10 Net Wealth/Housing effect on consumption - By income quintile

	2002 urban	**2013 urban**	**2002 rural**	**2013 rural**
Net Wealth*Income 1st quintile	0.065***	0.178***	0.093***	0.216***
	(0.0092)	(0.0092)	(0.0100)	(0.0072)
Net Wealth*Income 2nd quintile	0.070***	0.186***	0.094***	0.220***
	(0.0091)	(0.0090)	(0.0098)	(0.0070)
Net Wealth*Income 3rd quintile	0.072***	0.192***	0.098***	0.224***
	(0.0090)	(0.0089)	(0.0097)	(0.0070)
Net Wealth*Income 4th quintile	0.076***	0.197***	0.103***	0.230***
	(0.0091)	(0.0089)	(0.0097)	(0.0070)
Net Wealth*Income 5th quintile	0.078***	0.204***	0.111***	0.237***
	(0.0092)	(0.0089)	(0.0097)	(0.0069)
	2002 urban	**2013 urban**	**2002 rural**	**2013 rural**
Net Housing*Income 1st quintile	0.025***	0.108***	0.075***	0.154***
	(0.0060)	(0.0074)	(0.0059)	(0.0050)
Net Housing*Income 2nd quintile	0.030***	0.117***	0.077***	0.159***
	(0.0058)	(0.0072)	(0.0056)	(0.0047)
Net Housing*Income 3rd quintile	0.033***	0.122***	0.083***	0.163***
	(0.0058)	(0.0071)	(0.0055)	(0.0047)
Net Housing*Income 4th quintile	0.037***	0.127***	0.090***	0.170***
	(0.0059)	(0.0071)	(0.0055)	(0.0047)
Net Housing*Income 5th quintile	0.039***	0.135***	0.100***	0.178***
	(0.0061)	(0.0072)	(0.0057)	(0.0048)

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: See Table 4. All regressions also include control variables for household income, family size, age of household head, educational level of household head and provincial dummies.

Table 3-11 Net Wealth/Housing effect on consumption - By wealth quintile

	2002 urban	2013 urban	2002 rural	2013 rural
Net wealth*Net wealth 1st quintile	0.046	0.214***	0.119***	0.215***
	(0.0281)	(0.0236)	(0.0242)	(0.0188)
Net wealth*Net wealth 2nd quintile	0.050	0.208***	0.116***	0.214***
	(0.0261)	(0.0221)	(0.0228)	(0.0176)
Net wealth*Net wealth 3rd quintile	0.048	0.208***	0.115***	0.214***
	(0.0251)	(0.0212)	(0.0221)	(0.0169)
Net wealth*Net wealth 4th quintile	0.049*	0.209***	0.117***	0.214***
	(0.0242)	(0.0205)	(0.0215)	(0.0164)
Net wealth*Net wealth 5th quintile	0.053*	0.210***	0.116***	0.219***
	(0.0232)	(0.0195)	(0.0207)	(0.0156)
	2002 urban	**2013 urban**	**2002 rural**	**2013 rural**
Net Housing*Net wealth 1st quintile	0.017	0.085***	0.068***	0.130***
	(0.0107)	(0.0148)	(0.0095)	(0.0089)
Net Housing*Net wealth 2nd quintile	0.021*	0.084***	0.070***	0.133***
	(0.0095)	(0.0135)	(0.0085)	(0.0080)
Net Housing*Net wealth 3rd quintile	0.019*	0.088***	0.070***	0.135***
	(0.0089)	(0.0129)	(0.0080)	(0.0075)
Net Housing*Net wealth 4th quintile	0.020*	0.091***	0.075***	0.137***
	(0.0084)	(0.0123)	(0.0076)	(0.0071)
Net Housing*Net wealth 5th quintile	0.025**	0.096***	0.077***	0.145***
	(0.0079)	(0.0116)	(0.0071)	(0.0067)

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: See Table 4. All regressions also include control variables for household income, family size, age of household head, educational level of household head and provincial dummies.

3.8. Conclusion

We find evidence of a positive and significant effect of wealth on consumption. Overall, the marginal propensity to consume out of net wealth is highly significant and increases for both urban and rural households between 2002 and 2013, suggesting an increase in the importance of household net wealth to consumption over the two years. Estimates show that a one-yuan increase in household net wealth increases annual consumption in the range of 0.2 yuan in the short run in 2013.

Since housing is the main component of household wealth, it is not surprising that the effect of home value on household consumption is also strong. Our findings imply that net housing asset elasticity is 0.124 for urban households and 0.169 for their rural counterpart in 2013. In marked contrast, the estimated elasticity of consumption with respect to financial assets is much smaller and elusive over the two years. A potential explanation for this is the high correlation between financial wealth and current income, which makes it difficult to precisely identify the separate impact of each variable.

The pooled model provides further evidence that compared to the wealth elasticity for urban households, the wealth effect is much stronger in rural areas in both 2002 and 2013. A possible reason to interpret this finding is the larger effect of household income on consumption for urban households. Consequently, current income may be more important in the determination of household consumption in urban areas. Further the larger housing wealth elasticity for rural households is consistent with this interpretation. In terms of the year-specific effect, results from pooled data indicate that both for urban and rural households, the estimated sensitivity of consumption to net wealth and to net housing asset increases over the two years, while the estimated sensitivity of consumption to financial asset considerably increases only for rural households during this period.

Taking the heterogeneity of the wealth effect across different groups of households into account, we find that turning to 2013, both the net wealth and housing equity elasticity are smaller for younger households while much larger for prime age households, and older households as well, a result that can be interpreted as illustrating the differential need for precautionary saving and wealth accumulation across different age groups.

4. Targeting Performance of China's Rural Minimum Living Standard Guarantee Program

4.1. Introduction

With an aim to guarantee people a minimum living standard, China's Rural minimum living standard guarantee programme (or rural Dibao program) was adopted in 2007, and has been developed rapidly in the next ten years. Recent estimates from the Ministry of Civil Affairs (MOCA) report that the total spending on rural Dibao program exceeded 87 billion yuan and the program covered 29.4 million rural households (52.1 million rural beneficiaries) by the year 2014[34]. Although the central funding for this program increases, the income thresholds and transfer amounts are set by local officials based on local fiscal capacity and resources[35]. The goal of this program is to provide an unconditional cash transfer to the poor below an income threshold, i.e. households living in absolute poverty. Along with the changing structure of poverty in rural China, the proportion of poor households with household

[34] See 2014 Social Service Development Statistics Bulletin > reported by the Ministry of Civil Affairs ". The national average Dibao line is 2777 yuan per person per year in 2014. But the Dibao threshold for each province is quite diverse. For instance, the Dibao income threshold is the lowest for Henan province (1824.05 yuan per person per year), and the highest in Beijing (7587.69 yuan per person per year).

[35] The central government announced that the rural Dibao program was implemented nationwide in all counties and with central subsidies in early 2007, indicating that the local officials have the power to select the eligible individuals and provide them with cash transfers.

members who are unable to work has been increasing, so the rural Dibao program is of great importance to lift the poor out of poverty. China has set the goal to eliminate poverty by 2020, and is caring out the “Precise Poverty-Alleviation Strategy” (*Jingzhun Fupin*). Among the current poverty alleviation policies, the rural Dibao program is treated as an insurance program(*doudi*). Despite its great importance, the study of the targeting effectiveness of this program is still scare. Thus, how about the targeting performance of China’s rural Dibao program in actual practice? It highly depends on the targeting accuracy of this program. The targeting performance of this program is not only directly related to achieving the goal of eliminating poverty by 2020, but also to the realization of the national well-off strategic goal. Therefore, does the rural Dibao program cover all the poor below the income thresholds? Does the Dibao program really target the households living in the absolute poverty? In order to answer these questions, a central focus of this paper is to evaluate the targeting effectiveness of the rural Dibao program.

According to the Regulations on the Minimum Living Standard Guarantee Program>, the rural beneficiaries are the rural residents whose per capita net income is lower than the income threshold which is set locally at the county level. However, in actual practice, additional information about the household is also used to evaluate eligibility, such as household assets, the presence of household members who are unable to work, or of illness or disability, as well as the presence of natural disasters (the Ministry of Civil Affairs). But all these factors do not have a clear uniform standard. Therefore, there are some differences in identifying potential beneficiaries in different counties based on different selection criterion, which are leading to high inclusionary and exclusionary targeting errors. For instance, usually the recipients are selected by counting off incomes ranked from highest to lowest and choosing the poorest in some county(city), whereas other counties(cities) take all the villagers to vote the beneficiaries. Although both the income and non-income criteria are taken into account in the actual identification process, the targeting performance of the rural Dibao program is hardly comparable in part because of the differences in the selection criterion. On the other hand, unlike the official poverty line, the minimum income thresholds are set up at the county level based on the local fiscal capacity and resources. Consequently, there is not a national uniform Dibao line for all the counties[36]. Thus poor counties set lower Dibao thresholds and transfers than rich counties do and can not guarantee all the poor households living in absolute poverty.

The Dibao Program is one of the largest cash transfer programs in the developing world (Golan et al., 2014). Recently, with an increase in income thresholds and the number of beneficiaries, more and more scholars focus on the rural Dibao program and evaluate its effectiveness of targeting. However, due to data limitation, the existing literature on the targeting analysis remains relatively rare, and mostly based on small sample or case study. Through conducting a field interview in Shaxian County in Fujian Province, Li *et al.* (2006) find that there exists selection bias and targeting errors in the Dibao program, which is mainly due to the unclear selection criteria for identifying recipients. Based on a survey in a village in Anyang City, Ling and Liang (2009) find that the eligibility rate of this program was only 65.63%. And they

[36] So, it is the case that If the local fiscal capacity and resources are sufficient, and the local leaders give full attention to the Dibao program, the Dibao line tend to be much higher, otherwise lower. This can also be proved through the comparison of Dibao lines published on the Ministry of Civil Affairs website. Mainly due to differences in the level of economic development among provinces, the income thresholds are quite different. Overall, the Dibao lines are higher in the eastern areas while lower in the western region.

document that it is mainly due to the difficulty of measuring household incomes, as well as the irregularities in Dibao implementation. Deng and Wang (2008) also find high targeting errors based on a survey in 33 counties(cities) conducted by Wuhan University. Then on the basis of current targeting mechanisms for the potential recipients, they propose a new targeting method which combines the "hard system" (income thresholds) and "soft environment" (rural residents with food and shelter problem, living in illness or suffering from some sort of disaster) when identifying eligibility. Zhang (2010) also proves the existing high targeting errors in poverty areas in Chongqing, showing that the share of households with pre-income higher than the Dibao line is only 65.63% while the proportion of dibao households with pre-income below the local Dibao thresholds is only 14.8%. Using a household survey in Henan and Shaanxi Province in 2010, Han and Xu (2013) compares the targeting efficiency based on traditional poverty identification strategy and multidimensional poverty identification strategy. They find that the targeting errors are severe when identifying recipients based merely on income thresholds, but after taking other variables, such as household structure, human capital and household assets, into account, the measurement errors become acceptable[37]. Based on a survey of the elder in rural China, Hu *et al.* (2015) find that the targeting effectiveness is high for elderly people in rural areas. Using China household income survey in 2007, 2008 and 2009, Golan *et al.* (2014) find that although rural Dibao

[37] They find that over 70% of the poor did not receive Dibao transfers and the leakage to the non-poor (the share of the non-poor in all the Dibao households) is 65.74% using the traditional poverty identification strategy. However, when the multidimensional poverty identification strategy is adopted, the targeting efficiency is improved significantly, showing that the exclusion error and inclusion error decreased to 42.28% and 42.32%, respectively.

provides sufficient income to the poor, the inclusionary and exclusionary targeting errors are still large. They also estimate the impact of rural Dibao on poverty and carry out simulations to analyse the impact of increasing the local Dibao lines to a national level, and the simulation results show that it has the potential to reduce poverty, but the extent depends critically on targeting[38].

The contribution of this paper is threefold. First, the main focus of this paper is to investigate the targeting performance of the rural Dibao program. Unlike small-scale dataset or case study used in the previous literature, we employ a large scale rural household survey (the China Household Income Project 2013), which is representative and gather all the detailed information of households with dibao transfers. Second, our result reveals quite large targeting errors of this program using traditional income identification criteria. However, according to the actual practice of the rural Dibao program, identification of the eligibility should also take other information into account. We then observe that there exists a bias between policy design and implementation, and propose some suggestions for policy improvement. Third, on the basis of the actual selection process of the rural Dibao program, we put forward a new range of observable characteristics to identify potential beneficiary households, from the perspective of the Multidimensional Poverty Index. We employ this

[38] They find the exclusion error is around 89% to 94% while the inclusion error is about 86% to 94%. Then after applying the propensity score targeting analysis, both the inclusion and exclusion errors yield smaller errors but the targeting errors is still large.

multidimensional identification criterion into the data and prove that the targeting performance increases, which provides an empirical evidence for the policy reforms.

Using the latest household survey data and a new set of multidimensional criterion, this paper examines the targeting performance of the rural Dibao program. The structure of this paper proceeds as follows: Section 2 describes the data we use and compares household characteristics of households received Dibao transfers and poor households. We also discuss the Dibao targeting results on a basis of income identification strategy in this section. Section 3 reports the targeting performance of the Dibao program using the multi-dimensional identification criterion. Last, we conclude our findings and the implications for policy in Section 4.

4.2. Data

4.2.1. Data description

For the targeting analysis of the rural Dibao program, we use rural household survey data in the year 2013 (CHIP 2013) collected by the China Institute of Income Distribution. The rural survey sample contains around 10,490 households in 12 provinces and 2 province-level municipalities[39], which is also a subset of the National Bureau of Statistics (NBS) annual rural household survey. The dataset includes detailed information on household composition and demographics, household structure and employment, income and its components (including

[39] CHIP2013 covered 12 provinces and 2 province-level municipalities, including Beijing, Liaoning, Jiangsu, Shandong, Guangdong, Shanxi, Anhui, Henan, Hubei, Hunan, Gansu, Sichuan, Chongqing and Yunnan.

social assistance and subsidy, especially the minimum livelihood guarantee subsidy, i.e. Dibao transfers), as well as many other variables. It should be noted that the income data in CHIP2013 were collected using a diary method, containing wage income, business income, property income and transfer income. Also all the respondents should record the Dibao transfers. After cleaning outliers, the sample size is 10,068 rural households[40]. In the dataset, the number of households receiving Dibao transfers in 2013 is 697, and they account for 6.92% of the total number of households. According to the 2014 Social Service Development Statistics Bulletin > reported by the Ministry of Civil Affairs, there are around 29 million households and 54 million individuals who received Dibao transfers in 2013. And based on the 2014 Statistical Yearbook>, the amount of rural residents by 2013 is about 630 million (according to the location). Then it can be calculated that the coverage rate for the rural Dibao program is about 8.56%. If using rural *hukou* registration to calculate the rural residents, the coverage rate is around 6%. Therefore, The Dibao participation in CHIP2013 is just a little lower than that reported by the Ministry of Civil Affairs, which suggests that the CHIP sample has a strong representation.

Table 1 shows household's per capita income of all the permanent residents[41], of the Dibao households in the CHIP sample, as well as the Dibao line[42] across the 14 provinces

[40] The CHIP sample also includes rural samples in Xinjiang Province, but because of the lack of information on consumption and household assets for these samples, we exclude them from our analysis

[41] Here, migrant workers who had been working outside for more than 6 months are excluded when calculating permanent residents.

[42] Regarding the Dibao lines, we use administrative data published by the Ministry of Civil Affairs. These data are available at the county level and change every four months. Thus, we use the year-end (December) values of the

(municipalities). Due to the differences in local fiscal capacity and conditions, the level of the local Dibao thresholds vary substantially among provinces. It is clear that the Dibao income thresholds tend to be higher in eastern areas, such as Beijing, Jiangsu and Guangdong provinces. Whereas the Dibao lines are much lower in the western region, such as Sichuan, Hubei and Gansu provinces. When compared to the household income per capita in the CHIP dataset, the household income per capita is substantially higher than the local income thresholds in all provinces, and for most of the provinces the income thresholds are less than 25% of household per capita income. Even in Beijing, the Dibao line was only 31% of household income per capita. Moreover, pre-income is also calculated using the household income minus the amount of Dibao transfers received by the household. Again, pre-income per capita is much higher than the Dibao income thresholds for Dibao recipients. Among all the provinces, the difference between Dibao line and income per capita (for Dibao households) is the largest for Henan and Anhui provinces, while relatively smaller for Jiangsu and Guangdong provinces.

We further estimate the eligibility rate, i.e., the share of households with pre-incomes below the local Dibao income thresholds, and it is only 3.70%. It seems that the eligibility rate is not very large. However, it should be noted that the eligibility rate here is endogenous since the estimation is only based on household income deducting the Dibao transfers, while the other transfer income is always correlated with Dibao transfers. In fact, the eligibility rate increases to 8.7% when deducting the personal transfer income (including pensions and old-age insurance income), and further raises to 13.3% when deducting all the transfer income

county-level Dibao thresholds and calculate yearly Dibao lines (Yuan per person per year). Then we obtain the Dibao lines in the 199 surveyed counties.

(including living allowance, reimbursement for healthcare expenses, etc.). Also, not surprisingly, the eligibility rates are much higher in Gansu, Liaoning and Jiangsu provinces, while much lower in Henan and Guangdong provinces[43].

Table 4-1 Household Income and Dibao Thresholds (Yuan per person per year)

Province	(1) Income per capita	(2) Income per capita for Dibao households	(3) Dibao Thresholds	(4)＝(3)/(1)	(5)＝(3)/(2)	Eligibility rate
Beijing	19401	11121	6019	31.02	54.12	4.90
Shannxi	9718	5449	2076	21.36	38.10	3.72
Liaoning	12697	7707	2623	20.66	34.03	6.48
Jiangsu	16819	7276	4993	29.69	68.62	6.31
Anhui	12141	9724	2026	16.69	20.84	3.37
Shandong	15194	7065	2710	17.84	38.36	2.89
Henan	11524	8965	1772	15.38	19.77	1.28
Hubei	13013	9396	2004	15.40	21.33	2.03
Hunan	11821	6370	1862	15.75	29.23	2.76
Guangdong	15669	6340	3676	23.46	57.98	1.44
Chongqing	10542	4333	2394	22.71	55.25	4.98
Sichuan	10797	7973	2217	20.53	27.81	2.86
Yunan	11475	6140	1924	16.77	31.34	3.04
Gansu	7955	6041	1839	23.12	30.44	9.06
Full Sample	12763	7242	2608	20.43	36.01	3.70

Sources: "Income per capita" and "Income Per capita for Dibao households" are from the CHIP2013 sample. "Dibao Thresholds" is calculated using the administrative data published by the Ministry of Civil Affairs.

Notes: 1) All calculated over households. 2) Both the "Income per capita" and "Income per capita for Dibao households" are calculated using pre-incomes (excluding Dibao transfers). 2) The "eligibility rate" is the share of households with pre-incomes below the local Dibao income thresholds.

[43] For Henan Province, the Dibao line is the lowest (1,772 Yuan). It is mainly due to the limited local fiscal capacity which causes the lowest Dibao threshold, as well as the lowest eligibility. Regarding Guangdong Province, the income threshold is higher than that in other provinces, but compared to its household income per capita, it is still much lower.

4.2.2. The Targeting Effectiveness of rural Dibao

The stated goal of the rural Dibao program is to top up the beneficiaries' incomes to the level of local income threshold. Therefore, in the actual practice, the Dibao program should not only cover all eligible individuals, but also exclude the ineligible recipients from this program in time. In terms of "eligibility", there is divergence between the program's implementation and policy. According to the national policy, the Dibao program should perfectly target to the individuals whose income are below the local Dibao line, which uses household income as the only selection criteria. However, in practice, mainly due to the difficulties in accurately measuring household income, village leaders usually make use of a range of observable characteristics to identify potential beneficiary households, such as household composition, assets or consumption. In other words, the multi-dimensional identification criterion has been affecting the selection of recipients, as well as the targeting effectiveness of this program. It may also indicate that the targeting performance is poor based on the income identification strategy, but turn to be modest if using the multi-dimensional criterion to identify eligibility.

Moreover, it should be noted that the local Dibao threshold is not equal to the official poverty line [44]. So we also evaluate the targeting effectiveness using the poverty line as the identification criteria, to estimate the extent to which the Dibao program target the poor. Given a concern that the aim of the rural Dibao program is to bring the recipients' income to

[44] Regarding whether the Dibao thresholds should be based on the local income thresholds or the official poverty line causes controversy (Wang 2006). In this paper, we use the two standards to evaluate the targeting effectiveness of the rural Dibao program.

the income threshold, so if the local Dibao thresholds are smaller relative to the poverty line, this program will not effectively lift all the poor out even though the targeting accuracy is high.

To deal with these concerns, we estimate the effectiveness of targeting of the Dibao program using both local Dibao thresholds and the official poverty line.

Local Dibao Thresholds

First, we estimate the targeting performance of the rural Dibao program using local Dibao thresholds as the identification criteria, that is, based on the pre-incomes and the local income thresholds to calculate the inclusionary and exclusionary targeting errors. In this paper, we define Dibao households as households who received dibao transfers in 2013, and the eligible households are households with pre-income below the local Dibao thresholds. Then following the existing literature, **the inclusionary targeting error** refers to the share of households whose pre-incomes are above the local Dibao threshold with respect to all the Dibao households in the CHIP sample, and **the exclusionary error** is the percentage of eligible households being excluded from this program with respect to all the eligible households (Dellaportas G.,1980; Chen et al.,2006; Golan et al.,2014. In addition, we also estimate **the targeting accuracy**, i.e., the proportion of eligible households with Dibao transfers in all the Dibao households in the CHIP sample, and **the coverage effectiveness** which is the share of eligible Dibao recipients (with pre-income below the Dibao line and receiving dibao transfers) in all the eligible households.

Table 2 shows the estimated results of the targeting performance of the Dibao program across China's three major regions (eastern, central and western). Overall, using the local Dibao thresholds as the only identification criteria, either the inclusion errors or the exclusion errors are large while the coverage effectiveness is relatively small. In all the 697 households with dibao transfers, the share of eligible households is only 9.18% (64 households). And the inclusionary and exclusionary targeting error of the rural Dibao program reach as high as 90.82% and 82.61%, respectively. Also, this table reveals targeting differences among the three regions. The exclusion error is the highest in the eastern region while the lowest in western region. By contrast, the inclusion error is the highest in the central region but the lowest in the eastern region.

As reported in the table, the targeting performance of the rural Dibao program is poor. The possible explanations for the high inclusionary and exclusionary targeting errors are twofold. First, mainly due to the limited fiscal capacity of local governments or the irregularities in practice[45], this program can not cover all the eligible individuals. Second, the main selection criteria -the income identification strategy- is not that important when identifying the potential beneficiaries, while other selection criteria do.

[45] The flexible design of the Dibao implementation gives local officials considerable discretionary power, and create the potential for irregularities as well. According to reports by Chinese media, Dibao irregularities are numerous, such as giving Dibao to relatives or friends (guanxi bao, renqing bao), cheating (pian bao), or mistakes (cuo bao).

Table 4-2 Targeting Performance of the rural Dibao program (%)

Region	Dibao Thresholds				Poverty Line		
	Targeting Accuracy	**Coverage effectiveness**	**Exclusionary Error**	**Inclusionary Error**	**Poverty Rate**	**Exclusionary Error**	**Inclusionary Error**
Eastern	13.40	9.15	90.85	86.60	3.40	86.44	83.51
Central	5.63	17.35	82.65	94.37	5.06	83.25	89.07
Western	11.41	26.56	73.44	88.59	8.52	78.32	83.56
Full Sample	9.18	17.39	82.61	90.82	5.40	81.89	85.94

Source: Author's calculation from CHIP 2013

Notes: 1) The household incomes are calculated using pre-incomes (excluding Dibao transfers). 2) According the NBS, the poverty rate is 8.5% in 2013. However, here we just consider income poverty, thus the poverty rate is lower.

The Official Poverty Line

The rural Dibao program should go hand in hand with the poverty alleviation program to reduce the overall level of poverty in rural China. The poverty alleviation program is under the administration of the State Council Leading Group Office of Poverty Alleviation and Development, and the poverty guideline is set at the national level. By contrast, the Dibao lines are set locally at the county level in light of fiscal capacity and resources. Therefore, in some counties the Dibao lines are higher than the poverty line while others are not[46]. So how is the targeting performance of the rural Dibao program if it works using the poverty line as a uniform identification criterion? To what extent does the Dibao program target the poor?

[46] Although the standard of Dibao thresholds increases all the time, with a rapid annual growth rate of 7.11 percent, its average level is still lower than the official poverty line. For instance, the poverty line is 2800 yuan per person per year in 2014, while the Dibao line is 2777 yuan per person per year. However, at the regional level, only the Dibao thresholds in Beijing, Shanghai, Tianjin, Zhejiang, Jiangsu, Inner Mongolia, Guangdong, Hainan and Liaoning are higher than the poverty line, while the others are not.

Based on the 2013 official poverty line (2736 yuan per person per year), we estimate the inclusionary and exclusionary targeting errors (See Table 2). In this case, again, the inclusion and exclusion errors remain large, indicating that the majority of the poor do not benefit from the rural Dibao program.

According to the official poverty line, 541 households are identified as poor households in the CHIP sample. And as mentioned above, there are 697 households who received Dibao transfers in 2013. Thus, we find that the share of poor households receiving Dibao transfers is only 18.11% while the exclusionary targeting error is 81.99% (Table 3), indicating that the Dibao program did not well target the poor. On the other hand, because the objects of Dibao program and poverty alleviation program are not exactly the same, only 14.06% Dibao households have pre-incomes below the poverty line, which also implies that the leakage to the non-poor is large.

Table 4-3 Dibao Households and Poor Households (%)

	Poor Households	Non-poor Households
Dibao Households	18.11	6.29
Non-Dibao Households	81.89	93.71
	100	100
	Dibao Households	Non-Dibao Households
Poor Households	14.06	4.73
Non-poor Households	85.94	95.27
	100	100

Source: Author's calculation from CHIP 2013.
Notes: 1) "Poor Households" are defined as households with income per capita (excluding Dibao transfers) lower than the official poverty line in 2013. 2) "Dibao Households" are households received Dibao transfers in 2013.

The results above highlight the large targeting errors of the rural Dibao program when using income measurement as the only identification criterion. In actual practice, several reasons are held to interpret the large inclusionary and exclusionary targeting errors. First of all, in addition to household's income, the multi-dimensional identification criterion plays a central role in identifying the potential beneficiaries. Village leaders always make use of other information in local implementation practices, such as demographic composition, household assets or some sort of natural disaster. In other words, the role that the income criterion plays is not considerable while the multi-dimensional identification criterion does. We will discuss this issue in more details later. Second, as seen in Table 1, the Dibao lines are lower relative to the official poverty line in some poorer counties, leading to the insufficient coverage of the rural Dibao program. In these counties, even though the program benefits all the poor, other poor households with household incomes above the Dibao thresholds are still not covered. Third, the entry into and the existence of the rural Dibao program do not necessarily match. For instance, for households whose income is near the Dibao threshold or the poverty line, while their incomes may experience large fluctuation, the program does not have well function checks (Golan et al, 2014), and the adjustment of the beneficiaries does not catch up the growth of household incomes. So it is the case that some Dibao households are not poor households. Four, the measurement errors of household income may also raise targeting errors. In practice, accurately measuring household income is difficult. In rural areas, household incomes were more likely to be in the form of farming for earlier years. However, with an increase in the number of rural-to-urban migration, other forms of income such as wages and remittances are becoming a large proportion of household income, but it is hard to be grasped or screened. Moreover, there is time difference between survey-based incomes and those used in identifying eligibility (Chen et al., 2006), which may also cause targeting errors. Five, the Dibao irregularities are numerous (Golan et al.,2014). In practice, some local village and township cadres give dibao benefits to some relatives or friends on the basis of personal relationships (*renqing bao*), or even give dibao transfers to themselves by cheating (*pian bao*). So the Dibao work is not sufficiently transparent and open (Zhu, 2012), which may lead to the observed targeting errors of this program.

In terms of the possible reasons mentioned above, relatively, we care more about the first reason. In fact, if the village leaders select Dibao beneficiaries using the multi-dimensional identification criterion, it is consistent with the core of Multidimensional Poverty Identification Strategy, which is also a great progress in poverty alleviation programs. To confirm this assumption, the multi-dimensional identification criterion will be used to evaluate the targeting effectiveness of the rural Dibao program later.

4.3. Different characteristics of Dibao households and poor households

Based on the estimated targeting errors reported in the previous section, we can see that poor households include both Dibao and non-Dibao households, while Dibao households include both poor and non-poor households. Thus, we can divide all the CHIP sample into four types: Poor households with dibao benefits, Non-poor households with dibao transfers, Poor households without dibao transfers, and Non-poor households without dibao transfers. The first of the three types of households, accounting for almost 11% of the total sample, is the focus of our study. In the CHIP rural sample, 98 poor households received Dibao benefits, accounting for 0.97% of the total; 559 non-poor households (5.95% of the total 10,068 households) were Dibao recipients; and the proportion of the poor without Dibao transfers is 4.4% (443 households).

Table 4 contains descriptive characteristics of the three types of households of interest for us. By comparison, we find significant differences among the three types of households. The comparison of the poor with and without Dibao transfers reveals differences in household composition, housing conditions, household assets, as well as household consumption (Column 5 in Table 4), and all differences are statistically significant. It shows that household size and the number of children at school are smaller for the poor households with dibao benefits, and that the average education level of household adult members is much lower. They are also significantly less likely to have toilet facilities, they have fewer assets and spend more on health care. By contrast, the comparison of Dibao households, whether poor or not, shows that many of the characteristics are quite similar. For instance, they both contain markedly higher share of disability and less educated members (with educational attainment in primary school or below), and the age of the household head is older. In addition, the share of households with no toilet facilities is also much higher. In other words, more characteristics are likely to be taken into account when the local officials identify eligible Dibao beneficiaries, or they use the multi-dimensional identification criterion in reality. Although some Dibao beneficiaries had pre-incomes higher than the local dibao thresholds, they should also be targeted since the presence of household members who are ill or disable is higher. As a complement, based on the income criterion, we also compared the differences in characteristics among the eligible Dibao households (households with pre-income per capita lower than the income thresholds and receiving Dibao transfers), ineligible Dibao households (Dibao households with pre-income per capita higher than the income thresholds) and eligible households (with income per capita below the Dibao line) without Dibao transfers. We also find that the characteristics of Dibao households, whether the households are eligible or not based on income thresholds, are quite similar. It shows that both the eligible Dibao households and the ineligible Dibao households contain higher share of disable and less educated members, as well as a higher share of medical consumption, and the share of households with no toilet facilities is much higher. By contrast, Dibao households are quite different compared to eligible households without Dibao transfers. This also indicates that although according to the income thresholds some households should not be targeted by the program, the presence of household members who are of ill or disable is markedly higher.

Table 4-4 Summary Statistics for Dibao and Poor Households

Household Composition	**Dibao &Poor (1)**	**Dibao&Non-poor (2)**	**Non-Dibao&Poor (3)**	**T-test (1)&(2)**	**T-test (1)&(3)**
Total income in the past two years(Yuan)	31951	45571	56123	(-)***	(-)***
Permanent Residents	3.09	3.08	3.54	NS	(-)***
Number of children at school	0.56	0.49	0.90	NS	(-)***
Age of household head	59.06	57.02	54.19	NS	(+)***
Share of less educated members (%)	62.74	57.38	46.90	NS	(+)***
Share of illness (%)	31.59	26.52	10.67	NS	(+)***
Share of disability (%)	10.20	9.37	3.26	NS	(+)***
Housing					
No toilet facilities (%)	7.29	5.72	1.38	NS	(+)***
Household Assets					
Productive fixed assets(Yuan)	7167	5925	16518	NS	(-)**
Financial assets(Yuan)	10837	17427	25235	(-)*	(-)***
Housing value(Yuan)	50084	78993	87794	(-)**	(-)***
Consumption					
Budget share of medical consumption(%)	8.45	11.47	6.78	(-)**	NS

Source: Author's calculation from CHIP 2013.

Notes: 1) "Poor Households" are defined as households with income per capita (excluding Dibao transfers) lower than the official poverty line in 2013. 2) "Dibao Households" are households who received Dibao transfers in 2013. 3) The last column reports the significance level of mean differences (NS: non-significant; *: significant at 10%; **: significant at 5%; ***: significant at 1%). 4). The symbols in parentheses display the positive/negative differences between the two groups.

4.3.1. Characteristics associated with the rural Dibao participation

To further examine our assumption that the multi-dimensional identification criterion is affecting the selection of Dibao recipient households in practice, we estimate a Probit model to explain the characteristics associated with Dibao status, using the three types of households mentioned above. The model is specified as follows:

$$\mathrm{Prob}(P) = \alpha + \beta_i X_i + \varepsilon_i$$

The independent variables contain 16 relevant attributes including household income (total income in the past two years, i.e., the total income for the year 2011 and 2012), household composition (the number of permanent residents, the number of children at school, share of illness, share of disability), human capital (share of less educated members), household head characteristics (age of household head), housing condition (absence of toilet facilities), physical capital (productive fixed assets, financial assets and net housing assets) and household consumption (medical expenditure per capita). In addition, provincial dummies are also controlled accounting for unobservable variables at the provincial level. Here, we estimate two models. In the first model, we rely on samples including only ineligible Dibao households (with pre-income higher than the income thresholds) and poor households with Dibao transfers, trying to estimate the characteristics associated with ineligible identification using traditional income criteria. So the dependent variable in the Column 1 is 1 if the Dibao household is ineligible (with pre-income higher than the local Dibao thresholds), and 0 if the households are poor and with Dibao transfers. For the second model, using only ineligible Dibao households and poor households without Dibao transfers, we focus mainly on the characteristic that effect the identification of the ineligible Dibao households. Hence, the dependent variable in the Column 2 is 1 if the Dibao household is ineligible, and 0 if the households are poor but without Dibao transfers. Table 5 reports the estimated results of Probit regressions.

Probit regressions reveal that the differences in ineligible Dibao households based on the local Dibao thresholds and poor household with Dibao transfers are not significant. By contrast, when comparing to the eligible households but excluded from the rural Dibao program, many of the characteristics in Column 2 are statistically significant predictors. For instance, the variables such as the number children at school, the share of household members who are in bad health or disabile and the average consumption on medical care, are positively and significantly associated with the probability of receiving Dibao transfers. Our result indicates that although some Dibao households are not eligible based on the Dibao income thresholds, the characteristics of these households are similar to the poor households receiving Dibao benefits, and it is reasonable that these households are targeted on the basis of other variables besides income. Hence, besides household income, local officials seems to adopt other selection criteria to decide about the eligibility of the rural Dibao program, including household composition, the presence of household members who are disable or living condition.

Table 4-5 Probit Regression

	(1) Ineligible-Dibao HH/Poor-Dibao HH	(2) Ineligible-Dibao HH/Poor but Non-Dibao HH
Household income	-0.000*	-0.000
	(0.0000)	(0.0000)
Number of permanent residents	0.118	0.022
	(0.0697)	(0.0427)
Number of children at school	0.136	-0.213**
	(0.1205)	(0.0725)
Age of Household Head	0.006	0.005
	(0.0066)	(0.0044)
Share of less educated members	-0.203	0.251
	(0.2383)	(0.1582)
Share of illness	0.563*	0.857***
	(0.2454)	(0.2122)
Share of disability	-0.457	1.014**
	(0.4087)	(0.3555)
Without Toilet(dummy)	0.289	0.670
	(0.2964)	(0.3421)
Productive fixed assets	0.000	-0.000**
	(0.0000)	(0.0000)
Financial assets	-0.000*	-0.000
	(0.0000)	(0.0000)
Net housing assets	-0.000	-0.000
	(0.0000)	(0.0000)
Medical expenditure per capita	-0.000	0.000*
	(0.0001)	(0.0000)
Province	YES	YES
Constant	-5.176	-1.196**
	(197.4717)	(0.4242)
Sample Size	693	933
Adjusted R2	0.1477	0.2578

Source: Author's calculation from CHIP 2013.

Notes: 1) Estimation 1 is done on a sample including only ineligible Dibao households and poor households with Dibao transfers, to investigate the characteristics associated with ineligible identification using traditional income criteria. 2) Estimation 2 is done on a sample that includes ineligible Dibao households and poor households without Dibao transfers, to estimate the characteristic affecting the identification of the ineligible Dibao households. 3) Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

As can be seen from the above results, it seems that a better measure of eligibility is used in implementing the program, namely, the multi-dimensional identification criterion. Based on the findings above, there is no doubt that using the multi-dimensional identification criterion will affect the targeting effectiveness of the program. However, since there is no formal regulation in terms of the multi-dimensional identification criterion in implementation, it gives officials at the county, township and village level considerable discretionary power, which in turn may also leadto targeting errors in the actual practice. We then examine the targeting performance of this program using the multi-dimensional identification criterion. In other words, does the program target all the eligible households on the basis of the multi-dimensional identification criterion, and if so, to what extent? How about the targeting errors? We will discuss these questions in the next section.

4.4. The analysis of Dibao targeting on the multi-dimensional criterion

In the actual selection process, besides income, the program also targets eligible households on the basis of other variables. Consequently, there exists targeting bias using the Dibao lines as the only selection criterion. The existing literature also includes that using income as the only identification strategy is the main reason causing targeting errors (Chen *et al.*,2006; Golan *et al*., 2014). To further analyze the targeting performance of the rural Dibao program, we carry out a targeting analysis on the basis of the multi-dimensional identification criterion. And we propose a better measure of eligibility, from the perspective of this criterion.

4.4.1. Definition of Multidimensional Poverty

In terms of poverty, it is widely accepted that although income is an important measure to identify the poor, poverty is a multidimensional phenomenon. More and more scholars are focusing on multidimensional poverty rather than one-dimensional income poverty, to better target all the eligible poor households. In a pioneering paper, Amartya Sen first proposed that poverty is not the mere lack of income, but deprivation in basic human capabilities of the individuals or family, and that the deprivation of basic capabilities is multidimensional (Sen, 1992). Therefore, he proposes an axiomatic approach to identify the poor through the concept of multidimensional poverty. According to the multidimensional poverty measurement, not only income, but also the education, health, living standards and the provision of public services dimensions contribute to multidimensional poverty. On a basis of the multidimensional analysis of poverty and the concrete situation in rural China, we apply a methodology developed by Alkire and Foster(2007) to estimate multidimensional poverty in rural China. As detailed in Table 6, four dimensions and seven indicators are taken into account in measuring multidimensional poverty.

Regarding the education dimension, we define both the share of educational expenditure and the drop out of school-aged children as the main indicators. In the existing literature, there are two sorts of measures to estimate the share of educational expenditure, namely, the proportion of education expenditure with respect to household income or household consumption. In this paper, we employ the first measure, that is, the share of educational consumption is defined as the proportion of expenditure on education to household total income (before Dibao transfers).

In this section, we will use a multidimensional poverty index (MPI). All the selected cut-offs and weights for each dimension are based on the specific characteristics of rural poverty and anti-poverty policy in rural China. Relative to the developed countries, the development level is quite low for rural China, so consumption (income) poverty still occupies a very important role, and the main issue for anti-poverty is to solve the "poor" problems. Thus consumption poverty is weighted at 40%. Secondly, according to the current poverty problems in rural China, poverty is mainly caused by illness or lower education. As a consequence, the health poverty is weighted at 30% while education poverty holding 20% weight. Last, the weight of the housing dimension is 10%.

Table 4-6 Definition of the Multidimensional Poverty Index

Dimension	Definition of Indicators and cut-offs	Weights
1.Education	Share of educational expenditure in income larger than 0.5;	10%
	If any school-aged(7~15) children is out of school；	10％
2.Health	If any household member is of disability；	10%
	If any household member is of illness；	10%
	Budget share for medical care is larger than 0.5；[47]	10%
3.Housing	If household does not have toilet facilities;	10%
4.Consumption	Household per capita consumption is lower than 3000 Yuan	40%

[47] In the full sample, the average budget share of medical with respect to the household total consumption is 16.79%. Thus, here we define households with three times higher share of consumption on medical care as the poor households.

4.4.2. Targeting effectiveness of Dibao program in one dimension

Based on the deprivation cut-offs defined in Table 6, we present the distribution of multidimensional poverty and targeting effectiveness of the rural Dibao program in one dimension (Table 7). Table 7 shows that when taking the educational dimension as the threshold, the incidence of multidimensional poverty in the CHIP sample is 4.04%. 11.33% households are poor measured by the health dimension, and 4.97% of the sampled households are deprived in terms of consumption. Overall, among the four selected dimensions, the response rate to health deprivation is highest, followed by the consumption and educational dimensions.

Table 4-7 Targeting Performance of Dibao program in one dimension

	Dimension	Poor HH (1)	Poverty Rate (%) (2)	Dibao HH in each dimension (3)	Coverage Effectiveness (3)/(1)	Targeting Accuracy (3)/697 Dibao HH
1	Education	345	3.43	26	7.54	3.73
		61	0.61	5	8.20	0.72
2	Health	595	5.91	144	24.20	20.66
		246	2.44	45	18.29	6.46
		300	2.98	42	14.00	6.03
3	Housing	219	2.18	41	18.72	5.88
4	Consumption	500	4.97	72	14.40	10.33
Total		1,988	19.85	29348		

Source: Author's calculation from CHIP 2013.

Notes: 1) "Poor Households" are muldtidimensionally poor households, which are defined based on the Multidimensional Poverty Index mentioned above. 2) "Dibao Households" are households received Dibao transfers in 2013. 3) "Coverage Effectiveness" is the share of Dibao households with respect to the multidimensionally poor households. 4) "Targeting Accuracy" is the proportion of eligble households with Dibao transfers in all the Dibao households in the CHIP sample.

As seen in Table 7, the total incidence of multidimensional poverty in CHIP sample is 19.85% when taken into account only one dimension and sum up all the poverty rates. However, among all the 1,988 multidimensionally poor households, the amount of Dibao recipients is 293, accounting for only 14.66% of the total 697 dibao households in the sample. On the other hand, among all the 697 households with Dibao transfers, the proposition of multidimensionally poor households (deprived in any one of the four dimension) is only 42.04%. That is, according to the standard of the multidimensional poverty, the targeting accuracy of the rural Dibao program is around 42%. A detail description of the targeting

[48] It should be noted that although the total of this column is 377, there are some households who are deprived in more than one dimension. Actually, the total amount of Dibao household that belong to the multidimensionally poor.

accuracy in the four dimensions is also shown in Table 7. It reveals that the poor households in health benefit the most from the Dibao program, while the targeting error of the Dibao program is largest for poor households in consumption dimension (the targeting accuracy is only 10.33%).

Moreover, Table 8 presents the extent to which the poor households received Dibao benefits and to which the Dibao program benefited the poor. Again, the poor households are multidimensionally poor households calculated if the household is deprived in any one of the four dimensions. Among all the multidimensionally poor households, the proportion of households benefiting from the Dibao program is only 14.7%, implying low coverage of the Dibao program. But the share of multidimensionally poor households in Dibao households is 42%, which can be viewed as the effectiveness of the Dibao program. Thus, relatively to the income poverty, the Dibao effectiveness based on the analysis of multidimensional poverty increases.

However, it should also be noted that after applying the multidimensional poverty measurement, both the number of poor individuals and the poverty rate increase. Then in this case, if the selection criterion of Dibao program is still based on household income, there is no doubt that the number of eligible individuals is much smaller than that of multidimensionally poor individuals, especially in poorer areas.

Table 4-8 Targeting Performance using multidimensional poverty measurement (%)

	Poor Households	Non-poor Households
Dibao Households	14.66	5.01
Non-Dibao Households	85.34	94.99
	100	100
	Dibao Households	Non-Dibao Households
Poor Households	42.04	18.19
Non-poor Households	57.96	81.81
	100	100

Source: Author's calculation from CHIP 2013.

Notes: 1) "Poor Households" are muldtidimensionally poor households, which are defined based on the Multidimensional Poverty Index mentioned above. 2) "Dibao Households" are households received Dibao transfers in 2013.

4.4.3. Targeting effectiveness of the Dibao program in the multidimensional case

According to the conceptual framework for multidimensional poverty analysis, we can use the Multidimensional Poverty Index (MPI) to measure the degree of deprivation of each household and the poverty rate in the CHIP sample. The measurement of poverty involves the following steps: (1) Select dimensions, as well as the indicators in each dimension; (2) Identify the "cut-offs" for each dimension and judge whether a household is deprived with respect to this dimension or not; (3) Determine the weight for each dimension; (4) Calculate the sum of weighted deprivations suffered by household *i*, which is also viewed as the poverty score (incidence of poverty) for this household. So it is clear that the more higher score one household gets, the higher the poverty degree. Finally, on the basis of the poverty score, we can define whether or not the household is poor through setting different poverty cut-off *k*.

Here, each household gets a poverty score according to its characteristics and the Multidimensional Poverty Index we discussed above. For instance, if a household is only deprived in terms of educational expenditure (i.e., the share of educational expenditure in income is larger than 0.5), since the weight of the educational expenditure is 0.1, so the poverty score for this household is 0.1. In addition, if a household is deprived both in terms of educational expenditure and consumption dimension, and the weights for these two dimensions are 0.1 and 0.4, reprehensively, so the poverty score for this household is 0.5. It should be noted that k is the cut-off, and we set different levels of k to evaluate the targeting effectiveness of the rural Dibao program.

According to the measure of multidimensional poverty, we then define the multidimensional poor households using different kinds of cutoff *k*, as well as the corresponding incidence of multidimensional poverty and the targeting accuracy of the rural Dibao program. Table 9 shows the contribution of each dimension using the Multidimensional Poverty Measurement[49], and Table 10 presents the targeting result. Clearly, when using the poverty cut-off of *k=0.1*, around 13.44% of the CHIP sample were multidimensional poor, while only 13.75% of these multidimensional poor households benefited from the rural Dibao program. If we select poverty cut-off with *k=0.2* (Considering any two of the three dimensions except the consumption dimension[50]), the coverage effectiveness of the Dibao program is 22.22%,

[49] It should be noted that since in this section we do not employ equally weighted dimensions, so the poverty rate does not decrease along with the increasing *k.*

[50] The weight for consumption dimension is 0.4. Thus if a household is deprived in terms of consumption, the poverty score should be at least 0.4.

indicating that only 22.22% of the multidimensional poor households received Dibao transfers in 2013. When taking *k=0.3*, the coverage effectiveness increases to 50%. Then in a case with *k=0.4* (Taking all the four dimensions into account, including households who are only deprived in consumption), the incidence of multidimensional poverty is 3.96%, while the coverage effectiveness is 10.03%. Overall, among all the 1,988 multidimensional poor households, 293 of them benefited from the Dibao program, accounting for 42% (of the total 697 Dibao households) in the CHIP sample. In other words, the targeting accuracy of the Dibao program is 42% on the basis of the analysis of the multidimensional poverty identification. However, on the other hand, the coverage effectiveness remains quite low, indicating that only 14.66% of the multidimensional poor households received Dibao transfers in 2013, while 85.34% were excluded from the program. The result implies that the majority of the multidimensional poor households did not benefit from the rural Dibao program.[51]

Table 4-9 Poverty Rate and the contribution of each dimension using the Multidimensional Poverty Measurement (%)

		Contribution of each dimension(%)			
K	Poverty Rate	Education	Health	Housing	Consumption
0.1	13.44	24.8	62.5	12.6	0.0
0.2	1.34	18.5	70.4	11.1	0.0
0.3	0.10	23.3	76.7	0.0	0.0
0.4	3.96	0.0	0.0	0.0	100.0
0.5	0.89	5.0	37.8	7.2	50.0
0.6	0.10	7.5	32.5	10.0	50.0
0.7	0.01	25.0	25.0	25.0	25.0

[51] In addition, we also evaluate the targeting performance of the rural Dibao program using equally weighed dimensions, and the results are quite similar.

Table 4-10 Coverage Effectiveness and Targeting Accuracy using the Multidimensional Poverty Measurement

K	Poor HH (1)	Dibao HH (2)	Coverage Effectiveness (%) (2)/(1)	Targeting Accuracy (%) (2)/ Dibao HH
0	-	404	-	57.96
0.1	1353	186	13.75	-
0.2	135	30	22.22	-
0.3	10	5	50.00	-
0.4	399	40	10.03	-
0.5	90	23	25.56	-
0.6	10	8	80.00	-
0.7	1	1	100.00	-
Total	1998	293	14.66	42.04

Source: Author's calculation from CHIP 2013.
Notes: 1) "Poor Households" are muldtidimensionally poor households, which are defined based on the Multidimensional Poverty Index mentioned above. 2) "Dibao Households" are households received Dibao transfers in 2013. 3) "Coverage Effectiveness" is the share of Dibao households with respect to the multidimensionally poor households. 4) "Targeting Accuracy" is the proportion of eligble households with Dibao transfers in all the Dibao households in the CHIP sample.

4.4.4. Policy bias and improvement

The results above imply that relative to the mere income identification, the targeting performance of the Dibao program is much better using the multidimensional identification criterion. It also indicates that in practice, the selection of eligible Dibao households is affected by the multidimensional poverty strategy while the income measure is weakening. That is, local village committees identify potential beneficiaries using a multi-dimensional identification criterion, which is in line with the concept of Multidimensional Poverty and a great progress in Precise Poverty Alleviation program (*Jingzhun Fupin*).

However, on the other hand, even under the multi-dimensional identification criterion, yet over 80% of the poor cannot benefit from the Dibao program. There are several possible reasons for the observed divergence. First, although central funding of the rural Dibao program increased, the income thresholds continued to be set at the county level, depending much more on the local fiscal capacity. Consequently, the Dibao thresholds tend to be lower in some poor counties, which cannot target all the poor households in rural areas, and lead to some leakage to the poor. Second, in practice, some county (village) officials were confused about the income identification and the multidimensional identification criterion in Dibao implementation. Although local officials make use of a range of information, i.e., the multidimensional criterion, to evaluate eligibility, yet there is no uniform set of standards for local government to carry out. So targeting errors still remain. Third, there are differences between the policy design and its implementation. Clearly, the program beneficiaries should be selected based on current year household incomes, but due to difficulties accurately measuring income, most localities are likely to use the multidimensional criterion in practice. As a result, the number of Dibao households is much lower than that of the multidimensional poor households, which is the main reason causing the large targeting error.

Therefore, to achieve “perfect Dibao targeting”, we suggest to further improve the identification strategy of the rural Dibao program in the selection process, and well-functioning checks in dynamic adjustment. On one hand, the local governments should increase Dibao funding and expand its coverage, to bring the low-income households above the income thresholds and lift them out of poverty. On the other hand, we should further strengthen the combination of the theory of Multidimensional Poverty and implementation, trying to apply the concept of Multidimensional Poverty. Meanwhile, policy makers should set a uniform range of standards for local governments to carry out, replacing the existing local thresholds.

4.5. Conclusion

This paper examines the targeting performance of China's Rural minimum living standard guarantee programme, one of the most important program for poverty alleviation. Using the rural household survey data in the year 2013 collected by the China Institute of Income Distribution, we first compare the differences in characteristics among rural Dibao households, the ineligible Dibao households, the eligible households excluded from the Dibao program, and then examine the targeting effectiveness of the rural Dibao program using the traditional income identification. In the CHIP sample, 697 households received Dibao transfers in 2013, accounting for 6.92% of of the total. Then the comparison of Dibao households and poor households (based on the poverty line) reveals differences in household composition, household assets as well as other characteristics, indicating that the majority of Dibao households belong to the non-poor while most of the poor households are not Dibao recipients. This finding is consistent with the results in existing literature. We find that in practice, the multidimensional identification criterion is affecting the selection of beneficiaries for the rural Dibao program. In other words, beside income criteria, a range of other measures should also be taken into account to evaluate eligibility. Then we further estimate the targeting effectiveness of this program on the basis of the multidimensional identification criterion.

First of all, the comparison of Dibao recipients, whether poor or not, shows that many of the characteristics are quite similar. These households both contain markedly higher share of disable and less educated members, and the age of the household head is older. In addition, the share of households without toilets and the budget share of medical care is much higher. On the other hand, these characteristics are quite different with poor households without

Dibao transfers. The descriptive results indicate that the local officials identify eligible Dibao beneficiaries based on a concept of multidimensional poverty strategy, so it is necessary to analyze the targeting performance of this program using a multi-dimensional identification criterion.

Taking education, health, housing and consumption dimensions into account, we propose a new selection criterion, the multi-dimensional identification criterion, to evaluate the targeting effectiveness of the rural Dibao program. The result shows that the targeting accuracy of the Dibao program is 42%, indicating a marked increase in the targeting effectiveness. However, it should be noted that when using the multidimensional poverty measurement, both the number of poor individuals and the poverty rate increase. And in this case, although the targeting performance is better, more than half of the multidimensional poor households are excluded from the Dibao program.

The first requirement for the Precise Poverty Alleviation program is to better target all the poor. According to the results above, the targeting errors remain large either using the income criteria or the multi-dimensional identification criterion. So we suggest that policy makers should set a uniform range of standards for local governments to carry out, on the basis of the concept of Multidimensional Poverty Index. In addition, local governments should increase the amount of funding for the rural Dibao program and expand its coverage, especially in poor areas, to bring the low-income households above the income thresholds and lift them out of poverty.

5. General Conclusion

A central focus of this thesis is rural household consumption issues. We first analyze the effect of migration and remittances on school decision and educational investment, and then study the wealth effects on household consumption. The last focuses on the poverty problems faced by rural households and evaluates the targeting performance of the poverty alleviation policy, the rural Dibao program.

5.1. The impact of migration and remittances on educational investment

The **first chapter** aims at investigating the effect of migration and remittances on school enrollment and educational investment in rural China. Using household data from the China Household Income Project 2013, we find that both migration and remittances play a negative role in educational decision, which highlights the net adverse effect of the absence of parental migrants in the household. But remittances can act as an insurance mechanism since the amount of remittances is associated with higher enrollment. Moreover, the results also provide evidence that both migration and remittance decisions adversely affect educational investment, and households with migrants or remittances tend to spend much less on compulsory education. One reason may be related to the decision to migrate, which always happens in less affluent households and is always simultaneous with the decision to remit, for explicit purpose, such as health care. Meanwhile, migrant-sending/ remittance-receiving households are in favor of investment in assets which may immediately improve their quality of life, such as housing. The other explanation is due to the lower quality and returns to education in rural China, thus households may view educational investment as a consumption good. Given our results, we suggest that policy makers should take some action to improve the educational investment in rural areas, especially for poorer households. And education officials should improve the quality of education in rural China.

5.2. Wealth and Household Consumption

The **second chapter** concentrates on the wealth effect on consumption and its changes between 2002 and 2013. The results reveal a positive and significant effect of wealth on consumption, and we also find an increase in the importance of household net wealth to consumption for both urban and rural households over the two years, showing that a one-yuan increase in household net wealth increases annual consumption in the range of 0.2 yuan in the short run in 2013. Moreover, the descriptive result reveals that housing is the main component of household wealth, so it is not surprising that the effect of home value on household consumption remains strong. Our findings imply that the net housing asset elasticity is 0.124 for urban households and 0.169 for their rural counterpart in 2013. But the estimated elasticity of consumption with respect to financial assets is much smaller and elusive over the two years, which is mainly due to the high correlation between financial wealth and current income. Then the heterogeneity of the wealth effect across different groups of households shows that turning to 2013, both the net wealth and housing equity elasticity are smaller for younger households while much larger for prime age households, and older households as well, and it can be interpreted as illustrating the differential need for precautionary saving and wealth accumulation across different age groups.

5.3. The rural Dibao Program and Its effect on Poverty

The **third chapter** evaluates the targeting performance of the rural Dibao program. Using the rural household survey data in the year 2013 collected by the China Institute of Income Distribution, we first compare the differences in characteristics among rural Dibao households, the ineligible Dibao households, the eligible households excluded from the Dibao program, and then examine the targeting effectiveness of the rural Dibao program using the traditional income identification. The comparison of Dibao households and poor households (based on the poverty line) reveals that the majority of Dibao households belong to the non-poor while most of the poor households are not Dibao recipients, indicating that the targeting erros of the Dibao program is quite large. The descriptive results imply that the local officials identify eligible Dibao beneficiaries based on the concept of multidimensional poverty strategy. In other words, in practice, the multidimensional identification criterion is affecting the selection of beneficiaries for the rural Dibao program. Besides income criteria, a range of other measures should also have been taking into account to evaluate eligibility. Then taken education, health, housing and consumption dimensions into account, we propose a new selection criterion, the multi-dimensional identification criterion, to evaluate the targeting effectiveness of the rural Dibao program. The results show that the targeting accuracy of the Dibao program is 42%, indicating a markedly increase in the targeting effectiveness. So we suggest that policy makers should set a uniform range of standards for local government to carry out, on the basis of the concept of Multidimensional Poverty Index. In addition, local government should increase the amount of funding for the rural Dibao program and expand its coverage, especially in poor areas, to bring the low-income households above the income thresholds and lift them out of poverty.

5.4. Suggestions for policy reforms

Based on the empirical evidence from the chapters above, we put forward the following suggestions related to policy choice:

First of all, according to the existing results, we find that both migration and remittance decisions adversely affect educational investment. Given the importance of human capital investment in the labor market and the inevitable increase of rural to urban migration, it is worth noting that policy makers should take some action to improve the educational investment in rural areas, especially for poorer households. Some compensatory measures such as Minimum Living Standard Guarantee Program should target these households and improve their poverty situation and the absence of parents. Meanwhile, education officials should hire more qualified teachers to improve the quality of education in rural China. Ultimately, since the institution segmentation is the main factor causing this problem, the negative effect would be ameliorated if the children of migrants can get access to urban schools equally as urban children.

Secondly, we provide evidence of the positive effect of wealth on consumption, as well as the unequal increasing distribution of household wealth in rural areas. Therefore, in order to simulate consumption as well as reduce consumption inequality, we should promptly promote the reform of property distribution, especially for those “non-property farmers”.

Third, the rural dibao program can help to lift low-income households out of poverty, which depend highly on the targeting performance of this program. According to the bias between policy design and practice, we suggest to set a uniform range of standards for the rural Dibao program for local government to carry out, on the basis of the concept of Multidimensional

Poverty Index. In addition, local governments should increase the amount of funding for the rural Dibao program and expand its coverage, especially in poor areas. Therefore, it is necessary to increase Dibao funding and expand its coverage, so it can further help to reduce consumption inequality.

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Appendix A

Appendix Table A.1 Summary statistics–Children characteristics and Household characteristics

	(1)	(2)	(3)	T-test	T-test
	Non-migrant Non-receiving	Migrant receiving	Migrant Non-receiving	(1) VS (2+3)	(2)VS(3)
Characteristics of children					
Age	13.69	13.66	13.95	*	NO
Boy(%)	52.9	54.8	54.3	NO	NO
Older Age group(%)	26.9	28.9	32.2	NO	NO
boys aged 16~18(%)	14.5	15.5	16.9	NO	**
Household Composition					
Number of infants	0.177	0.205	0.161	NO	**
Number of children aged between 7 and 12	0.689	0.769	0.672	***	NO
Number of children aged between 13 and 15	0.397	0.373	0.351	NO	NO
Number of children aged between 16 and 18	0.389	0.461	0.470	NO	**
Number of members aged between 19 and 55	2.087	2.393	2.305	***	***
Number of members aged between 56 and 65	0.371	0.566	0.450	***	***
Number of members aged over 66	0.229	0.360	0.232	***	***
Household Characteristics					
Average age of adult members (years)	32.32	33.37	32.63	NO	***
Average education of adult members (years)	7.75	7.16	7.76	***	***
Member(s) with disability or chronic illness(%)	1.92	2.82	1.85	NO	*
Having at least a member with higher education(%)	69.2	66.0	66.2	NO	NO
Household Wealth					
Log of estimated housing value	11.63	11.41	11.66	NO	***
Total land	7.05	6.18	6.82	NO	NO

Notes: 1) "Infants in household" reflects the number of children below the age of 6. 2)"Older Age Group" indicates the percentage of children aged between 16~18. 3) *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Source: Child-Level database with children aged between 7 ~18. Author's calculation from 2013 China Household Income Project.

Appendix Table A.2 Summary statistics –Household characteristics

	(1)	(2)	(3)	T-test	T-test
	Non-migrant Non-receiving	Migrant receiving	Migrant Non-receiving	(1)VS (2+3)	(2)VS(3)
Household Composition					
Number of children at school	1.345	1.408	1.312	NO	***
Number of infants	0.241	0.338	0.288	***	*
Number of children aged between 7~12	0.507	0.574	0.499	*	**
Number of children aged between 13~15	0.281	0.272	0.248	NO	NO
Number of children aged between 16~18	0.269	0.274	0.284	NO	NO
Number of members aged between 19~55	2.246	2.619	2.560	***	NO
Number of members aged between 56~65	0.451	0.692	0.556	***	***
Number of members aged over 66	0.219	0.313	0.221	**	***
Household Characteristics					
Average age of adult members (years)	33.67	34.08	33.50	NO	*
Average education of adult members (years)	8.099	7.396	8.168	***	***
Member(s) with disability or chronic illness(%)	1.72	2.94	1.51	NO	**
At least a member with higher education(%)	20.1	14.4	21.8	**	***
Household Wealth					
Log of estimated housing value	11.70	11.41	11.72	***	***
Total land	6.657	6.348	6.443	NO	NO
Observations	1,982	1,090	795		

Notes: *Significant at 10% level, **Significant at 5% level, ***Significant at 1% level.

Source: Household-level database with at leas one child at school in 2013. Author's calculation from 2013 China Household Income Project.

Appendix Table A.3 Average Budget Shares by migrant and remittance status (%)

	Non migrant-sending	Migrant-sending	T-test
Budget share for food	43.51	45.12	***
Budget share for durable goods	16.67	14.87	***
Budget share for housing	19.29	19.80	NO
Budget share for education	14.89	13.73	*
Budget share for medical care	5.64	6.48	**
Observations	1,982	1,885	

	Non remittance-receiving	Remittance-receiving	Total
Budget share for food	43.42	46.53	***
Budget share for durable goods	16.54	13.90	***
Budget share for housing	19.53	19.56	NO
Budget share for education	14.76	13.21	**
Budget share for medical care	5.76	6.80	**
Observations	2,777	1,090	3769

Source: Household-Level database with at least one child at school in 2013. Author's calculation from 2013 China Household Income Project.

Appendix Table A.4 Regression Results (Migrant-sending vs Non migrant-sending)

	Non Migrant-sending Households				
	Education	Food	Durables	Housing	Health
Log of total expenditure	0.038***	-0.085***	0.063***	-0.033***	0.017***
	(0.0058)	(0.0057)	(0.0046)	(0.0052)	(0.0040)
Household Characteristics	YES	YES	YES	YES	YES
Province Dummy	YES	YES	YES	YES	YES
Constant	-0.501***	1.575***	-0.336***	0.254***	0.008
	(0.0674)	(0.0661)	(0.0538)	(0.0602)	(0.0468)
Observations	1982	1982	1982	1982	1982
Adjusted R2	0.235	0.266	0.122	0.215	0.036
	Migrant-sending Households				
	Education	Food	Durables	Housing	Health
Log of total expenditure	0.043***	-0.104***	0.058***	-0.024***	0.028***
	(0.0057)	(0.0058)	(0.0044)	(0.0052)	(0.0046)
Household Characteristics	YES	YES	YES	YES	YES
Province Dummy	YES	YES	YES	YES	YES
Constant	-0.624***	1.811***	-0.215***	0.096	-0.068
	(0.0712)	(0.0724)	(0.0543)	(0.0640)	(0.0569)
Observations	1885	1885	1885	1885	1885
Adjusted R2	0.247	0.294	0.114	0.199	0.049

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for household characteristics, household assets and provincial dummies.

Source: Household-level database with at least one child at school in 2013. Author's calculation from 2013 China Household Income Project.

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Appendix Table A.5 Regression Results (Remittance-receiving vs. Non remittance-receiving)

	Non Remittance-receiving Households				
	Education	Food	Durables	Housing	Health
Log of total expenditure	0.037***	-0.083***	0.065***	-0.034***	0.016***
	(0.0047)	(0.0046)	(0.0037)	(0.0042)	(0.0033)
Household Characteristics	YES	YES	YES	YES	YES
Province Dummy	YES	YES	YES	YES	YES
Constant	-0.523***	1.578***	-0.336***	0.251***	0.030
	(0.0564)	(0.0553)	(0.0448)	(0.0499)	(0.0396)
Observations	2777	2777	2777	2777	2777
Adjusted R2	0.236	0.253	0.130	0.209	0.042
	Remittance-receiving Households				
	Education	Food	Durables	Housing	Health
Log of total expenditure	0.058***	-0.127***	0.040***	-0.020**	0.049***
	(0.0085)	(0.0086)	(0.0062)	(0.0077)	(0.0072)
Household Characteristics	YES	YES	YES	YES	YES
Province Dummy	YES	YES	YES	YES	YES
Constant	-0.705***	2.175***	-0.127	-0.034	-0.308*
	(0.1493)	(0.1521)	(0.1096)	(0.1356)	(0.1265)
Observations	1090	1090	1090	1090	1090
Adjusted R2	0.246	0.354	0.076	0.230	0.056

Notes: 1) Standard errors in parentheses. 2)*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level. 3) All regressions also include control variables for household characteristics, household assets and provincial dummies.

Source: 2013 China Household Income Project. Household-level database with only one child at school in 2013.

Appendix Table A.6 – Household financial wealth prediction

Dependent variable: Household financial wealth	2002 urban	2013 urban	2002 rural	2013 rural
Age of household head	0.0162***	0.0111	0.0017	0.0424***
	(0.004)	(0.009)	(0.011)	(0.009)
Age square	-0.0000	0.0001	0.0000	-0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)
Education of household head	0.0558***	0.0785***	0.0215***	0.0371***
	(0.003)	(0.006)	(0.007)	(0.006)
Education of spouse	0.0397***	0.0372***	0.0365***	0.0634***
	(0.002)	(0.004)	(0.006)	(0.005)
Number of working adults	0.1812***	0.2054***	0.0698***	0.1807***
	(0.012)	(0.020)	(0.014)	(0.012)
Province dummies	Yes	Yes	Yes	Yes
Observations	6,294	5,976	8,953	10,079
Adjusted R2	0.1666	0.1824	0.1623	0.1453

Source: Author's calculation from CHIP 2002 and CHIP 2013

Note: Standard errors in parentheses. * *p* 0.05, ** *p* 0.01, *** *p* 0.001.

Appendix Table A.7 - Summary statistics

	2002 urban	**2013 urban**	**2002 rural**	**2013 rural**
Log income	9.88	11.10	9.34	10.17
Log wealth	11.78	13.04	10.97	11.95
Log housing wealth	11.14	12.72	9.84	11.19
Log financial wealth	9.97	10.58	8.04	9.81
Log other wealth	9.23	10.08	10.12	10.27
Household size	2.98	3.01	4.13	3.71
Age of household head	48.30	52.18	46.45	52.95
Education of household head (years)	10.91	10.63	7.15	6.95
Observations	4,672	4,647	8,736	9,231

Source: Author's calculation from CHIP 2002 and CHIP 2013.

Note: The sample excludes households reporting non-positive consumption and households with non-positive net wealth, non-positive net housing values or non-positive financial asset.

Appendix B

This appendix reinterprets the Working-Leser model in the text, which can be written as follows:

$$S_{ji} = \frac{C_{ji}}{Exp_i} = \beta_i + \gamma_i(logExp_i) + \varepsilon_i \quad (6)$$

where C_{ji} represents expenditure on good *j* in household *i*, Exp_i is the total consumption for household *i* , β_i and γ_i are the parameters to be estimated, and ε_i is the error term. Then S_{ji} reflects the average budget share of good *i*, and it requires $\sum C_{ji}/Exp_i = 1$. To investigate the effect of migration and remittances on educational investment, we compare the marginal budget shares of different consumption categories in different types of households. In addition, when comparing consumption behaviors, various variables such as household composition, household characteristics and geographic characteristics (province dummy) also need to be taken into account. Then a specification for this paper is:

$$S_{ji} = \beta_i + \gamma_i(logExp_i) + \sum \mu_i Z_i + \varepsilon_i \quad (7)$$

Z_i denotes the household characteristics which may influence the budget shares, for instance, the average age of adults, the average education of adults (years), whether the household has at least one member having higher education, household composition variables such as household size, the number of children below age 6, the number of children aged between 7 and 18, the number of household members aged between 56 and 65, the number of elderly (over the age of 66)[52], the logarithm of housing value and total agricultural land. Also, we use provincial dummies to control the unobservable variables that may affect the estimated results at the provincial level.

Taken from equation (7), the partial derivative of average budget shares with respect to the total expenditure can be derived as follows:

$$\partial S_{ji}/\partial Exp_i = \frac{Exp_i \frac{\partial C_{ji}}{\partial \ xp_i} - C_{ji} \frac{\partial \ xp_i}{\partial \ xp_i}}{Exp_i^{\ 2}} = \frac{\frac{\partial C_{ji}}{\partial \ xp_i}}{Exp_i} - \frac{C_{ji}}{Exp_i^{\ 2}} = \frac{\gamma_i}{Exp_i} \quad (9)$$

Then the marginal budget share for good *j* in household *i* can be written as follows:

$$MBS_{ji} = \partial C_{ji}/\partial Exp_i = \gamma_i + S_{ji} \quad (10)$$

Based on the definition of elasticity, the expenditure elasticity (η) is equivalent to:

$$\eta_{ji} = \frac{MBS_{ji}}{ABS_{ji}} = \frac{\gamma_i}{S_{ji}} + 1 \quad (11)$$

In practice, the estimation technique used in the first step is an OLS Model. As mentioned earlier, the household consumption components are aggregated into five consumption categories: 1) food; 2) durables goods; 3) housing; 4) education; 5) health care. Since in the samples two of the categories are censored at zero (education and health care consumption), then a censored Tobit approach may be more appropriate. However, the sample size censored

[52] Here, we use "the number of household members aged between 19 and 55" as the reference group.

at zero is very small (0.1% for education consumption and 5% for health care) and there is not much difference between these two models, so we view this small size as omitted variables in the estimation and employ OLS model.