HONG KONG INSTITUTE FOR MONETARY RESEARCH

HETEROGENEOUS PREFERENCES AND RISK SHARING AT HOUSEHOLD LEVEL IN CHINA

Jennifer T. Lai, Isabel K. M. Yan and Xingjian Yi

HKIMR Working Paper No.6/2018

February 2018

Heterogeneous preferences and risk sharing at household level in China

Jennifer T. Lai *
School of Finance, Guangdong University of Foreign Studies

Isabel K. M. Yan
Department of Economics and Finance,City University of Hong Kong

Xingjian Yi
School of Finance, Guangdong University of Foreign Studies

January 2018

Abstract

This paper investigates the degree of risk sharing across households in China with heterogeneous risk and time preferences from the late 1990s to early 2010s. Standard tests assume homogeneous preferences across households, which may bias the true risk sharing degree if, in reality, preferences correlate with variations of household income. We use household data from the China Health and Nutrition Survey (CHNS) and China Family Panel Studies (CFPS) to show that, in China, the incomes of less risk-averse and less patient households correlate more positively with the aggregate risk. The standard test, which ignores this correlation, shows about 30% of household income shocks pass through to household consumption. However, this number reduces to 3% and becomes insignificant when preferences heterogeneity is accounted for. By comparing this result with that of the US, we find the degree of risk sharing across households in China is similar to that in the US. We argue that this improvement of risk sharing from the standard test to tests with preferences heterogeneity is due to the institutional changes and labour market reforms that took place during the mid-1990s and early 2000s. This gave individuals more freedom in their labour market choices, which makes preferences heterogeneity more relevant, as people can choose occupations more aligned with their preferences. We then use the Research Center on the Rural Economy (RCRE) Fixed Point Rural Household Survey data to provide empirical evidence of the effect of reforms on household risk sharing.

Keywords: Consumption, risk sharing, heterogeneous preferences, insurance, China.

JEL classification: E21, E24

---

* Email addresses: Lai: econlai@gmail.com

We thank Heather Anderson, Hilde Bjørnland, Kenneth Chan, Charles Leung, Shi Li, Junjian Yi, and seminar participants at the Fourth Annual Conference of the International Association for Applied Econometrics, the 14th Chinese Finance Annual Meeting and many other venues for their helpful comments. This paper was initiated when Jennifer Lai was a visiting research fellow at the Hong Kong Institute for Monetary Research (HKIMR), whose hospitality is gratefully acknowledged. She thanks HKIMR and the National Natural Science Foundation of China (Project No. 71403061) for financial support. Xingjian Yi thanks the National Natural Science Foundation of China (Project No. 71373057) for financial support.

1. Introduction

China has experienced more than 30 years of high economic growth, with its average annual per capita GDP growth rate exceeding 8% from 1978 to 2012 (Zhu, 2012). At the same time, transformation of the economy to a more market-oriented one was accompanied by major policy changes that caused income risks to increase substantially during the past two decades (Chamon et al., 2013; Santaeulàlia-Llopis and Zheng, 2016). This prompts one to ask a question that has important welfare implications for households in China: in the presence of increased uncertainty, what is the ability of Chinese households to insure their consumption from increased income volatility?

Previous studies have been conducted to investigate this question. They could be classified into three main categories. First, since the ability of agents to insure their consumption against income risks is closely related to markets' completeness, one naturally resorts to tests of risk sharing to see if there is full insurance in China (Xu, 2008; Curtis and Mark, 2010; Du et al., 2011). Second, as China is in its transition to a market-oriented economy, it is hard to imagine that markets are complete in China, and empirical tests of complete risk sharing tend to reject full risk sharing. As a result, the standard incomplete markets model is usually assumed and one tries to empirically measure the degree of partial insurance of households in China (Santaeulàlia-Llopis and Zheng, 2016). This partial insurance of consumption against income is based on the fact that agents can achieve self-insurance by borrowing and lending at a fixed interest rate, while, on the other hand, agents can also share risks through private family networks, the public social insurance system and financial markets (Blundell et al., 2008). Third, many studies specifically focus on investigating the effects of self-insurance in China (Meng, 2003; Chamon et al., 2013; Choi et al., 2014; Chan et al., 2014).

The above-mentioned works have several points that need to be addressed. *First*, is it appropriate to assume a priori that conditions for full insurance are not satisfied? This is because, although formal markets are probably incomplete in China, there are a variety of informal channels that households could use to insure themselves against shocks (Townsend, 1994). Studies, such as Chiappori et al. (2014), show that degree of risk sharing is higher in rural Thailand than in the US. As such, whether an economy has more advanced markets does not seem to suggest a higher degree of risk sharing.

Second, standard risk sharing tests may produce biased estimated risk sharing coefficients due to the assumption of homogeneous preferences across households. It has been shown by Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) that, if people have heterogeneous risk preferences, those with less risk aversion may choose to bear more aggregate risk. Neglecting this effect will cause an upward bias in standard risk sharing tests[1]. This point is of particular importance for China for two reasons. First, households' income risk has increased substantially since the late 1990s [2]. Empirical studies show that households' income risk remained relatively stable untill the second half of the 1990s and started to quickly pick up afterwards (Chamon et al., 2013; Santaeulàlia-Llopis and Zheng, 2016). This timing coincides with several structural and social reforms implemented at that time, which gave individuals more freedom in their labour market choices[3]. It became less difficult for labour market participants to sort themselves into different occupations according to their own preferences from the late 1990s onwards, compared to before. As such, neglecting preferences heterogeneity when it is present and not constrained by institutional arrangements may lead to incorrect conclusions on household risk sharing in China, particularly when data after the late 1990s is used.

Third, most previous studies on testing risk sharing in China use aggregated macro level data. For example, Curtis and Mark (2010), Du et al. (2011) and Chan et al. (2014) use provincial-level consumption and output data to test the degree of risk sharing in China[4]. Ho, et al. (2015) employ city-level retail sales and output data to test risk sharing in China, while Xu (2008) utilizes aggregated household survey data to test provincial risk sharing in China. This is partly due to the fact that micro-level household data for the past couple of decades is not readily available in China.

[1] Time preference heterogeneity will also cause bias in the estimated risk sharing coefficient from standard risk sharing tests. The direction depends on whether people with more patience bear more aggregate risk or less.

[2] From 1989 to 2009, wage inequality measured by the Gini coefficient has increased from 0.26 to 0.38, while in the same period, the Gini coefficient for OECD countries changed from 0.30 to 0.31 (Meng, 2012; OECD, 2011) . At the same time, wider dispersion of income, especially labour income, leads to opportunities to raise aggregate productivity by concentrating work among more productive workers (Heathcote et al., 2008).

[3] Detailed discussion is provided in Section 2.

[4] Ho et al. (2010) and Lai et al. (2014) also employ provincial-level data to test consumption risk sharing in China.

However, aggregated data may not appropriately reflect what goes on at the micro level before aggregation (Deaton, 1992). Since the ultimate goal of risk sharing tests is to find out the ability of households to insure themselves against shocks, it is more appropriate to use household-level data.

This paper aims to test the degree of risk sharing at household level in China, taking into account the effects of heterogeneous preferences. By employing data from a relatively long household survey, which spans 1997 to 2011 and was collected by China Health and Nutrition Survey (CHNS), we empirically test if households in China share risks completely. In addition, we correct the potential bias in the standard risk sharing test induced by assuming homogeneous preferences. As such, we are able to address the above three problems simultaneously. We argue that this bias is negligible before the mid-1990s when labour markets in China were subject to strict regulations. In that time people did not have much freedom to reveal their preferences through their labour market choices, even though heterogeneous preferences might be present. However, this bias becomes salient after the mid-1990s when a series of labour market reforms took place, which gave people more freedom in their labour market choices. By using the econometric techniques developed by Schulhofer-Wohl (2011), which are suitable for panels with large cross-sectional units but a short time span, not only could we test whether there is complete risk sharing (or full insurance) across households in China, we could also measure the degree of risk sharing (or partial insurance) if complete risk sharing is rejected. In addition, by using data collected by the Fixed Point Rural Household Survey from the Survey Department of the Research Center on the Rural Economy (RCRE) which spans 1986 to 2013, we empirically test if institutional reforms implemented in the 1990s have any effect on household risk sharing in China.

Our main findings are as follows. *First*, when neglecting preferences heterogeneity, 30% of income risks pass through to consumption for households in China from 1997 to 2011 according to CHNS data. This is much larger compared to US households from PSID (Panel Survey of In-come Dynamics) data (Schulhofer-Wohl, 2011). After taking into account preferences heterogeneity, household risk sharing degree in China is comparable to that of the US. *Second*, the upward bias of the estimated risk sharing coefficient that ignores preferences heterogeneity is closely related to institutional changes and labour market reforms that took place during the 1990s in China. These reforms gave individuals more freedom in their labour market choices. Before the mid-1990s, when most of those reforms had not been initiated and people were constrained by institutional arrangements in terms of their labour market choices, whether preferences heterogeneity was accounted for or not does not have a significant effect on the estimated risk sharing coefficients. However, after the mid-1990s, neglecting preferences heterogeneity leads to a significantly positive bias in the estimated risk sharing coefficients. This shows that the effect of preferences heterogeneity on risk sharing depends on whether people can freely express their preferences through their labour market choices. This then induces correlations between preferences and income variations cross-sectionally and causes biases in the standard risk sharing test.

This paper is among one of the first attempts in the literature to test risk sharing at the household level in a large, developing nation, China, by considering the potential effects of preferences heterogeneity. This is an important step for us to understand economic transition and development in China. Preferences heterogeneity has been shown to have important effects on people's choices of occupation (Fuchs-Schündeln and Schündeln, 2005; Bonin et al., 2007; Schulhofer-Wohl, 2011). However, a prerequisite for it to play a significant role is that people have freedom of choice. Our empirical investigation shows institutional changes and labour market reforms help facilitate risk sharing across households in China through eliminating strict restrictions on labour markets.

The rest of the paper is organised as follows. Section 2 presents a brief description of the institutional background in China during the period we focus on. Section 3 presents the model. Section 4 presents data descriptions and empirical evidence showing whether heterogeneity in preferences has any effect on the correlation of household income with aggregate output at the household level in China. Section 5 presents the results of risk sharing tests. Section 6 concludes.

2. Institutional background

In this section we briefly outline the institutional background in China before and during the mid-1990s to early 2000s. We focus on reforms that have the potential to affect households risk sharing abilities.

2.1. Before the mid-1990s

China started its market-oriented economic reform in the late 1970s in rural areas. Collective farming under the commune system was abandoned and the household responsibility system adopted (Chow, 2004). This led to a significant increase in rural productivity, as households enjoyed residual claims to their own production efforts. In the mid-1980s, rural unemployment became a serious problem. Rural residents were encouraged to set up Town and Village Enterprises (TVEs), which helped absorb redundant labour from agricultural production (Huang, 2008). Meanwhile, the Chinese government started to set up Special Economic Zones (SEZ) in a few cities[5], which, coupled with development of cities, called for more labour input. Therefore, limited rural-urban migrants emerged (Meng, 2012), although, at the same time, city governments stringently restricted rural migrants (Zhao, 2003).

Since the collapse of the rural commune system, the Rural Cooperative Healthcare System (RCHS), which was attached to the commune system and provided basic healthcare services for commune members, also disappeared. This left the rural population more vulnerable to health shocks (Dong, 2009).

These reforms have two major effects on rural households' ability of risk sharing. First, the household responsibility system, development of TVEs and rural-urban migrants contribute to increasing rural households' risk sharing abilities. By letting households decide what to produce on their land, the household responsibility system facilitated income smoothing of rural households. In addition, TVEs and rural-urban migration provided income diversification opportunities from off-farm activity. All of these can help rural households manage income risks and improve their insurance and risk sharing abilities (Morduch, 1995).

However, the absence of a social insurance system, predominantly a healthcare system, adversely affects their ability to insure against health shocks.

2.2. From the mid-1990s to early 2000s

After experimenting with economic reforms in the 1980s, China continued its reforms in the 1990s, focusing on urban sectors. One of the major structural reforms during the mid-1990s was a policy called "Holding on to the Large, Letting Go of the Small", which aimed to privatise small and medium-sized state owned enterprises (SOEs) while retaining state control of large enterprises. After its implementation in 1995, industrial output share of state and collective sectors shrank from more than 90% in 1990 to 70% in 1997, and further reduced to 30% in 2008[6]. This was accompanied by massive lay-offs in the state sector in urban areas, and by a continuingly thriving

[5]The SEZ was a designated area in a city that enjoyed free import duties and export tax rebates for foreign investors.

[6]See China Statistical Year Book (2009) and cited also by Meng (2012).

urban private sector. From 1995 to 2001, an estimated 34 million workers were laid off from the state sector (Giles et al., 2006). However, employment share of private enterprises increased from 10% in 1994 to more than 50% in 2007 (Storesletten and Zilibotti, 2014). During the same period, rural-urban migration also picked up significantly. In 1995, the central government relaxed the rural-urban migration restrictions. The number of migrant workers in cities increased from 39 million in 1997 to 145 million in 2009 (Iyer et al., 2013). In addition, starting from the early 1990s, college graduates in China were gradually not assigned to job positions by central planning of the Ministry of Education, and this job assignment system was fully abandoned after 2000[7]. Meanwhile, in 1997, wholly private enterprises owned by entrepreneurs received the official accreditation.

These reforms have a profound effect on urban and rural households in China. As the urban labour market became more open to job seekers and employers of various kinds, and entrepreneurship was encouraged, Chinese citizens had more freedom on their occupation choices from the mid-1990s onwards. Rather than being strictly bound by *Hukou*, and other institutional restrictions, and having few job choice, it became possible for people to select jobs according to their preferences. As such, for less risk-averse individuals, it became easier for them to choose jobs that allowed them to bear more aggregate risk of the economy. This could facilitate risk sharing across households in China. As such, empirical tests of risk sharing need to take into account the potential effect of preferences heterogeneity.

Along with the structural reforms were reforms of the social insurance systems in urban and rural areas. After four years of pilot reforms, starting from 1994, the Basic Social Medical Insurance Scheme for Urban Employees was launched nationwide in 1998, which replaced the free medical service program founded in 1952. In addition, employment injury insurance and unemployment insurance were implemented in 1996 and 1999, respectively (Rickne, 2013). The basic pension scheme was implemented in 1997 for urban employees. All these were to replace the Labour Insurance Scheme (LIS) set up in 1951 for urban employees, which provided non-wage benefits to the urban workforce from cradle to death. The new social insurance systems for urban workers feature contributions from employees and employers, while the previous system required no premium payment from employees. For the urban unemployed, the Basic Social Medical Insurance Scheme for Urban Residents (BSMISUR) was trialled and a total of 88 cities joined until 2007. For

[7] See Ministry of Education webpage: http://www.moe.gov.cn/jyb_sjzl/moe_1695/tnull_190223.html.

rural residents, the New Rural Cooperative Medical Insurance Scheme (NRCMIS) was trialled in 2003 and then implemented throughout rural areas to provide health insurance to rural people. By 2007, 85.6% of counties in China had implemented the scheme, and 86.2% rural population in these counties had been enrolled (Dong, 2009).

Although the social insurance systems implemented so far cover a large share of the population, their effectiveness remains questionable. This is probably due to two reasons. First, the tax reforms implemented in 1994 dramatically increased the central government's share of tax revenues, which more than doubled from 22% in 1993 to 49-56% after 1994 (Lai et al., 2014). Meanwhile, revenue recentralization was not accompanied by expenditure recentralization, and the central government's share in total government expenditure fell from 30% in 1994 to 18% in 2010 (Lai et al., 2014). Since the social insurance reforms listed above involve contribution from the central and local governments, insufficient revenues at the subnational level could have impaired the implementation of these schemes[8]. As such, it is an empirical question whether social insurance provides effective insurance and risk sharing for households in China.

3. Tests of risk sharing and bias from heterogeneous preference

Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) show that efficient allocation of consumption in an economy assigns more risks to less risk-averse households. When preferences are heterogeneous among households, standard tests of efficient risk sharing in the literature that assume homogeneous preferences fail to capture the true Pareto-efficient allocation and tend to generate spurious rejections of efficient risk sharing[9]. We briefly show the bias of the standard risk sharing test below.

In an endowment economy populated with many households, if households are assumed to have time-separable expected utility with period utility of CRRA form, the Pareto-optimal consumption allocations can be expressed as below:

$$\log c_{it} = \frac{\log \lambda_i}{\gamma_i} + \frac{1}{\gamma_i}(-\log \rho_t) + \varepsilon_{it} \tag{1}$$

[8]See more discussion in Santaeulàlia-Llopis and Zheng (2016), footnote 14.

[9]Mazzocco and Saini (2012) consider heterogeneity in risk preferences, while Schulhofer-Wohl (2011) takes into consideration heterogeneity in risk and time preferences. This section draws largely from Schulhofer-Wohl (2011).

where c_{it} is the consumption of household i in time period t, λ_i is the Pareto weight of household i, γ_i is the degree of risk aversion of household i, and ε_{it} is the multiplicative measurement error of household consumption. $\rho_t = \frac{\mu_t}{\beta^t \pi(s_t)}$, where μ_t is the Lagrange multiplier of the economy's feasibility constraint, $\pi(s_t)$ is the probability of the occurrence of state s_t, and β_t is time preference which temporarily is assumed homogeneous.

Eq. (1) shows that, for more risk-averse households, aggregate shock ρ_t has a smaller effect on their consumption. One could test for efficient consumption risk sharing by adding households idiosyncratic variable X_{it} to eq. (1):

$$\log c_{it} = \frac{\log \lambda_i}{\gamma_i} + \frac{1}{\gamma_i} (-\log \rho_t) + \theta X_{it} + \varepsilon_{it} \tag{2}$$

If the estimated coefficient θ associated with X_{it} is not significantly different from zero, this becomes an indication of full insurance. One of the widely used household idiosyncratic variables is household income[10], $\log y_{it}$, where y_{it} denotes income of household i in period t.

One of the crucial assumptions made in standard risk sharing tests, as pointed out by Schulhofer-Wohl (2011) and Mazzocco and Saini (2012), is that households have identical risk preferences, $\gamma_i = \gamma$. Replacing γ_i by γ, and X_{it} by $\log y_{it}$, eq.(2) becomes:

$$\log c_{it} = \frac{\log \lambda_i}{\gamma} + \frac{1}{\gamma} (-\log \rho_t) + \theta \log y_{it} + \varepsilon_{it}^{equal} \tag{3}$$

The above equation is simpler in that the second term related to the aggregate shock now becomes a time dummy variable and has an identical effect on the consumption across households. However, if the true model is eq.(2) and one mistakenly estimates eq. (3), the error term in eq.(3) absorbs the heterogeneous effect of aggregate shock on household consumption:

$$\varepsilon_{it}^{equal} = \left(\frac{1}{\gamma_i} - \frac{1}{\gamma} \right) (-\log \rho_t) + \varepsilon_{it} \tag{4}$$

If $Cov\left(\log y_{it}, \varepsilon_{it}^{equal}\right) = 0$, the least square estimator of the coefficient on income in eq. (3) is unbiased. However, if $Cov\left(\log y_{it}, \varepsilon_{it}^{equal}\right) > 0$ (< 0),the estimator is biased upward (downward).

Assume that household income is determined by the following equation:

$$\log y_{it} = \phi_i \omega_t + \xi_{it} \tag{5}$$

[10]For example, Cochrane (1991) and Mace (1991) use this variable to test full insurance at household level in the US, and Townsend (1994) tests that in rural Thailand.

where ω_t is a common shock, ϕ_i is the semielasticity of household i's income to the common shock, and ξ_{it} is an idiosyncratic shock to household i's income[11]. Assuming that the distributions of ϕ_i and γ_i are stationary, and ξ_{it} and ε_{it} are i.i.d., we have:

$$\begin{aligned} Cov\left[\log y_{it}, \varepsilon_{it}^{equal}\right] &= -Cov\left[\phi_i\omega_t + \xi_{it}, \left(\frac{1}{\gamma_i} - \frac{1}{\gamma}\right)\log\rho_t + \varepsilon_{it}\right] \\ &= -Cov\left[\phi_i\omega_t, \left(\frac{1}{\gamma_i} - \frac{1}{\gamma}\right)\log\rho_t\right] \\ &= -Cov\left(\omega_t, \log\rho_t\right) Cov\left(\phi_i, \frac{1}{\gamma_i}\right) \end{aligned} \tag{6}$$

$Cov\left(\omega_t, \log\rho_t\right) < 0$, because 1). $Cov\left(\omega_t, \sum_i^N c_{it}\right) > 0$, as aggregate shock and aggregate consumption is quite likely to be positively correlated; 2).$Cov\left(\log\rho_t, \sum_i^N c_{it}\right) < 0$, because when aggregate consumption increases, the marginal value of it, which is represented by the Lagrange multiplier ρ_t, decreases. As such, $Cov\left[\log y_{it}, \varepsilon_{it}^{equal}\right] > 0$ if $Cov\left(\phi_i, \frac{1}{\gamma_i}\right) > 0$. That is to say, the estimated θ in eq.(3) is biased upward if income and aggregate shock are correlated more strongly for less risk-averse households.

Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) point out this bias in risk sharing tests in the literature which assume homogeneous risk preference. Schulhofer-Wohl (2011) also indicates that if households have heterogeneous time preferences, this leads to bias in the risk sharing test, which assumes the absence of this heterogeneity. By using similar derivations and temporarily assuming homogeneity in risk preferences, it can be shown that under time preference heterogeneity, bias of standard tests arises from $Cov\left(\phi_i, \log\beta_i\right)$, which is the correlation between time preferences and the strength of income variability with the aggregate shock. If $Cov\left(\phi_i, \log\beta_i\right) > (<)\ 0$, the incomes of those with more patience correlates more (less) positively with the aggregate economy, the estimator θ is biased upward (downward).

By using PSID and HRS (The Health and Retirement Study) data, Schulhofer-Wohl (2011) finds that people with less risk aversion sort themselves into jobs with incomes that are correlated more strongly with aggregate shock, so $Cov\left(\phi_i, \frac{1}{\eta_i}\right) > 0$. In addition, the result of the risk sharing test with heterogeneous time preferences shows that the estimated $\widehat{\theta}$ is biased upward when neglecting

[11] This assumption is key to illustrating that income responds more strongly to aggregate shocks for less-risk-averse households (Schulhofer-Wohl, 2011). However, in the partial insurance literature, ϕ_i is usually assumed homogeneous across households, see Blundell et al. (2013).

time preference heterogeneity, which indicates that, in the US, $Cov\left(\phi_i, \log \beta_i\right) > 0$.

In the next section, we use both China Health and Nutrition Survey (CHNS) and China Family Panel Studies (CFPS) data, both of which are household-level survey data, to test whether, in China, incomes correlate more strongly for people with less risk aversion or not. In addition, we also test whether incomes correlate more strongly for people with less patience or not. This would help shed light on potential bias in the estimator of θ when assuming the absence of preferences heterogeneity.

4. Risk and time preferences: Do they correlate with household income variability?

4.1. Risk preferences and household income

In this subsection, we empirically test whether less risk averse people tend to choose occupations with incomes that correlate more positively with aggregate shocks in China.

In the literature, there are two ways to gauge whether a person is more risk averse. The first is to elicit people's risk preferences by asking them hypothetical questions related to their future income process[12]. This has been used by the Health and Retirement Survey (US), several European household surveys, the Survey of Consumer Finance (US) and the China Household Finance Survey (CHFS)[13].

The second way is to infer people's risk preferences by examining their behaviours. Barsky et al. (1997) find that people who are less risk averse have more risky behaviours such as smoking, drinking and not having insurance. Similar correlation between risk aversion and risky behaviours has also been found by Anderson and Mellor (2008), Lusk and Coble (2005) and Guiso and Paiella (2008). As a result, risk preferences are usually proxied by people's behaviours, such as smoking, drinking, and wearing seat belt. For example, Cutler et al. (2008) proxy risk preferences by five measures of behaviours: smoking, drinking, job-based mortality risk, receipt of preventive health care, and use of seat belts.

[12] Jamison et al. (2012) provide a detailed survey on this topic.

[13] Although CHFS provides survey data on respondents' risk preferences, the current available wave consists of only one year, which makes it impossible to obtain income dynamics across time.

The China Health and Nutrition Survey (CHNS), which contains information on health related behaviors, income and other demographic information of households in China, provides us with information to proxy for risk preferences of households and to test whether that, for less risk averse households, their income correlated more positively with the aggregate economy[14]. It asks the following questions on respondents' health behaviours: 1). Do you smoke cigarettes or pipes? 2). Do you drink beer/alcohol/liquor? 3). Have you used preventive health services in the past four weeks? Based on the answers to these questions, we construct three dummy variables that are *smoking*, *drinking* and *preventive health service*, which could be used as proxies of risk preferences of surveyed adults.

For household income data, it covers income from various channels of households, including: 1). Labour earnings; 2). Agricultural income; 3). Business income; and 4). Capital income[15]. We compute household income (excluding transfer income) by summing up labour earnings of household members, agricultural income, business income and capital income at the household level. We then compute the real household income by inflating nominal income using the provincial Consumer Price Index with 2011 as the base year provided by CHNS. We further compute the adult-equivalent household income using the scale in Krueger and Perri (2006).

We restrict our analysis to households with a head whose age is between 20 and 65. We drop those households that appear less than three times in the survey. We trim the top and bottom 1% of households in terms of their position in income and consumption distribution in each wave. This gives us 16,813 observations for 3550 households[16].

We estimate the following specification:

$$\log(y_{it}) = \alpha_0 + \alpha_1 \cdot behaviour_{it} + \alpha_2 \cdot aggshock_t + \alpha_3 \cdot behaviour_{it} \times aggshock_t + \mathbf{x_{it}}\mathbf{\Phi} + \upsilon_{it} \quad (7)$$

where $aggshock_t$ represents aggregate economic performance, and is proxied by per capita GDP from China Statistical Yearbooks. Alternatively, we also use per capita personal consumption from national income as a proxy. $behaviour_{it}$ represents the behaviour dummy that proxies risk preference of the head of household i at time t. We use three alternative proxies for this variable, namely *smoking*, *drinking* and *preventive health care*, which correspond to the three health

[14] For more details of the dataset, see the website of the CHNS data: `http://www.cpc.unc.edu/projects/china/`.
[15] Detailed information on data compilation can be found in Appendix A.
[16] Table A1 in Appendix A provides summary statistics.

behaviour questions listed above, respectively. People who smoke, drink and do not use preventive health services are considered to be less risk averse. In addition, we control for household head's age, gender, marital status, ethnicity, years of education, occupation type, whether a cadre, whether with urban registration, family dependence ratio, plus a constant in $\mathbf{x_{it}}$.

The key parameter of interest in eq. (7) is α_3. When risk aversion is proxied by smoke or drink, a positive α_3 indicates that incomes of less risk averse individuals correlate more positively with the aggregate economy, and vice versa. However, when it is proxied by whether one used preventive healthcare services, a negative α_3 indicates less risk averse individuals bear more risk of the aggregate economy.

The estimated results are presented in Table 1 in which aggregate shock is proxied by per capita real GDP. Panel A presents the estimated coefficients of α_1, α_2 and α_3 when *smoke* is used as a proxy for risk preference[17]. The estimated $\widehat{\alpha}_2$ is significantly positively different from zero across the three columns where OLS, FE and RE estimation are used, respectively. In addition, the key parameter that we focus on, the estimated $\widehat{\alpha}_3$, is significantly positive in all three columns as well. This indicates that compared with people who do not smoke, incomes of those who smoke correlate more positively with the aggregate economy. This shows that for people with less risk aversion, their incomes correlate more positively with the aggregate risk.

Similar results are obtained when drinking is used as a proxy for risk preference. In Panel B of Table 1, the estimated $\widehat{\alpha}_3$ is positive and significant. As a result, incomes of those who drink are correlated more positively with the aggregate shock, which is consistent with results in Panel A.

Panel C presents the results when risk preferences are proxied by use of preventive health care services. People who used the preventive healthcare services are considered to be more risk averse. The estimated $\widehat{\alpha}_3$ is negative in all three cases. A negative $\widehat{\alpha}_3$ shows that for people who utilized preventive healthcare services, their incomes correlate less positively with the aggregate economy, which is consistent with the results in Panel A and B. One possible reason that $\widehat{\alpha}_3$ is not significant could be that utilization of preventive health care is measured with error, as such the estimated coefficient associated with it might be biased towards zero.

Table 2 presents the regression results when aggregate risk is proxied by per capita personal

[17] The estimated coefficients of the control variables are omitted to preserve space. They are available upon request.

consumption from the national income account. Consistent with the results presented in Table 1, we find that incomes are correlated more positively with aggregate risk for those who smoke, drink and do not use preventive health care services.[18].

4.2. Time preferences and household income

In Section 3, it is shown that when people have heterogeneous time preferences, the estimated risk sharing parameter will be biased if the assumption of homogeneous time preference is maintained. This bias depends on how discrepancies of time preferences lead to household incomes being correlated with the aggregate risk differently. If incomes correlate more positively with the aggregate risk for those who are less patient, the estimated risk sharing parameter is biased downward. Otherwise it is biased upward. In general, the direction of the bias caused by heterogeneous time preferences is also an empirical one. In this section we investigate at household level in China, whether incomes of those with less patience correlate more or less with the aggregate risk.

The question that arises is: how should we proxy for time preference? Fuchs (1982) conducted an experimental study and finds time preference correlates significantly with self-evaluation of overall health. For those who have higher self-evaluation of overall health, which means they consider themselves relatively healthy, they tend to have lower discount rate and be more patient[19]. As

[18]We also use alternative measures of real annual adult equivalent household income for estimation. Results are largely the same as shown in Table 1 and 2. They are not shown here but are available upon request. In addition, we use relevant data from another national wide household survey, China Family Panel Survey (CFPS), to run the regression. Again, results are similar compared to those presented in Table 1 and Table 2. They are not presented but are available upon request.

[19]Fuchs (1982) also found smoking was significantly positively correlated with time preference. People who smoke tend to be less patient and have higher discount rates. Sutter et al. (2013) find that for children and adolescents, patience is negatively correlated with consumption of cigarettes and alcohol. One problem of smoking being used to proxy for time preference is that, it has also been used as a proxy for risk preference. This may lead to an implied positive relation between risk tolerance and impatience: those who smoke have higher risk tolerance and higher impatience. In the literature, there seems to be no consensus on the relationship between risk and time preferences. Voors et al. (2012) find that in regions with violent conflict, there seems to be a positive correlation between risk preference and impatience. However, Anderhub et al. (2001) and Becker et al. (1964) find a significant negative relationship between risk preference and impatience. Wolbert and Riedl (2013) shows by experiment that although subjects who are less risk averse tend to be more patient, this correlation is only small and marginally significant. As such, we assume that these two preferences are orthogonal and smoking may not be a suitable proxy for time preference.

such, self-evaluated overall health could be used to proxy for time preference of a person.

Becker and Mulligan (1997) developed an endogenous time preference model that predicts wealth and patience are positively correlated. They argue that people with more assets have more incentive to invest more heavily in an attempt to appreciate future utilities. They empirically tested this hypothesis using US PSID households data and presented consistent results. As such, total assets could also be used as a proxy for patience.

The China Family Panel Studies (CFPS), a panel survey of around 15,000 households and 40,000 individuals in each wave from 2010 to 2012, contains the self-evaluation of overall health at individual level and total assets at household level, plus income at household level. This data could be used for an empirical test of whether those who have higher self-rated health or are wealthier (hence more patient) tend to have their incomes correlate more positively with the aggregate shock or not.

Each individual in CFPS is asked to self-evaluate their health condition by answering the following question: How would you rate your health status? Five choices are available: 1. Excellent; 2. Very good; 3. Good; 4. Fair; 5. Poor[20]. Those whose choices were smaller had higher self-rated health.

Data on household total assets and income is also collected in two waves[21]. We keep those households with a head aged 20-65. We drop those households whose incomes are at the top

[20]The options listed here are from the 2012 wave. In 2010 the options are: 1. Healthy; 2. Fair; 3. Relatively unhealthy; 4. Unhealthy; 5. Very unhealthy. A person whose self-rated health remains "fair" in the two waves would choose twoin 2010 but four in 2012. This increase in the status of self-rated health (decrease in health condition) based on 2012 options does not truly reflect the correspondent's self-rated health condition change. As a result, for those who chose three, or four or five in the 2010 survey, we reset them to five according to the closest option in 2012. For those who chose two we reset the answer to four. This would help keep the choices between the two waves fairly consistent.

[21]CHNS provides a question that also asks participants to evaluate their health condition. The question is: Right now, how would you describe your health compared to that of other people your age? The choices are: 1. Excellent; 2. Good; 3; Fair; 4.Poor. Data is available in all waves except the 2009 and 2011 wave. However, CHNS provides only limited information on a household's assets. Specifically, CHNS asks its participants if they owned or bought any semi-durable goods or farm machine during the interview, and collects this information into household asset data sets. We use this data to perform regression in eq. (8) as well.

or bottom 1%. This gives us 13,317 observations in two waves. Appendix A provides summary statistics.

We estimate the following specification:

$$\log(y_{it}) = \kappa_0 + \kappa_1 \cdot patience_{it} + \kappa_2 \cdot aggshock_t + \kappa_3 \cdot patience_{it} \times aggshock_t + \mathbf{x_{it}}\mathbf{\Phi} + \varsigma_{it} \quad (8)$$

where $patience_{it}$ denotes time preference of the head of household i in year t and is proxied either by the self-rated health of the household's head or by the household's total asset. Control variables $\mathbf{x_{it}}$ are similar as in eq, (7). κ_3 is the key parameter of interest. If $patience_{it}$ is proxied by self-rated health, a positive (negative) $\widehat{\kappa}_3$ indicates that for those whose self-rated health is poorer, their incomes correlate more (less) positively with the aggregate shock. This would cause the risk sharing coefficient to be biased downward (upward). If $patience_{it}$ is proxied by households total asset, then a positively (negatively) estimated $\widehat{\kappa}_3$ indicates that incomes of those who have more assets correlates more (less) positively with the aggregate shock, which causes the risk sharing coefficient to be biased downward (upward).

Table 3 presents the estimation results of eq. (8), in which aggregate shock is proxied by real per capita GDP. In Panel A, when patience is proxied by self-rated health, the OLS estimated $\widehat{\kappa}_3$ is -0.2710, while the FE and RE estimates are 0.0194 and -0.1747 respectively. However, all the estimates are not statistically significantly different from zero, which shows that, when patience is proxied by self-rated health, the evidence that people with different time preferences may have their incomes correlate differently with the aggregate shock is rather weak.

Panel B of Table 3 presents the results when patience is proxied by household's total assets. The first column shows that the OLS estimated $\widehat{\kappa}_3$ is -0.0030. The FE and RE estimates of $\widehat{\kappa}_3$ are -0.0161 and -0.0062 respectively, among which the FE estimate is statistically significantly different from zero. This indicates that, for people who are wealthier, their incomes tend to correlate less positively with the aggregate risk. Thess results show that, for people with more patience, their income correlates less positively with the aggregate shock. As a result, the estimated risk sharing parameter in the standard test would be biased downward.

Table 4 presents the estimation results when aggregate shock is proxied by per capita real personal consumption. The results remain similar as in Table 3.

To sum up, the above results in Section 4.1 and 4.2 show that for households with less risk averse and less patience, their incomes correlate more positively with the aggregate shock. However, the evidence of time preference heterogeneity is not as strong as that of risk preferences heterogeneity. In the next section, robust risk sharing tests are performed in which biases from risk and time preferences are adjusted.

5. Robust risk sharing estimation results

Section 3 shows briefly that if risk and time preferences are heterogenous and correlate with household income variability, risk sharing tests that assume homogeneous preference are biased. Section 4 presents evidence that in China, for those who are less risk averse, their incomes correlate more positively with the aggregate shock. For those who are more patient, their incomes correlate less positively with the aggregate shock. In this section, we apply robust estimation methods to obtain risk sharing estimates that are unbiased in the presence of preferences heterogeneity.

Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) provide two ways to perform unbiased risk sharing tests in the presence of heterogeneous preferences. Schulhofer-Wohl (2011) estimated eq. (2) by grouping households' preferences γ_i into the error term and treating them as nuisance parameters. Therefore there is no need to estimate the household specific γ_i. Schulhofer-Wohl (2011) uses the factor model and GMM estimation to estimate the risk sharing parameter θ. The factor model nests both the heterogeneous and homogeneous risk preferences cases, so one can easily test whether factor estimates of the heterogeneous preferences model differ from estimates of the homogeneous preferences model. By so doing one could test whether the hypothesis of homogeneity in preferences is violated. The trade-off for this benefit is that the factor model makes strong assumptions about the distribution of the error term. GMM estimation makes fewer assumptions on the distribution of the error term, but is only valid when risk preferences are heterogeneous among households. Schulhofer-Wohl (2011) apply these two methods to estimate consumption risk sharing across US households using the PSID dataset. The two approaches are suitable for datasets that have large N and small T. In addition, when the hypothesis of full insurance is rejected, the estimated $\widehat{\theta}$ could be interpreted as a measure of the extent of partial insurance.

Mazzocco and Saini (2012) estimated each household's preferences first and then test for heterogeneity in preferences and full insurance. They use a dataset that has a large T ($T \geq 100$), which allows them to make fewer assumptions of the functional form of the utilities. However, our dataset is not long enough, which makes the technique developed in Mazzocco and Saini (2012) not applicable.

In this section, we apply the factor model approach and GMM approach from Schulhofer-Wohl (2011) to estimate eq. (2) using CHNS data and test full insurance at household level in China[22].

5.1. Factor model estimation results

Table 5 presents the results of factor model estimation using CHNS data on real adult equivalent household consumption and real adult equivalent household income[23]. Household consumption here is measured by food consumption. Household income (excluding transfer) is measured as the sum of wage income, agricultural income, capital income and business income. Transfer income, whether from public channels (eg. government transfer, or transfer from work units) or private channels (eg. transfer between relatives and friends) is excluded.

Because self-reported household income data may be subject to measurement errors, the presence of which may bias downward the estimated risk sharing coefficient, we need to use a valid instrument for income so the potential bias caused by measurement error of income can be tackled. Otherwise, if we obtain a significantly positive $\widehat{\theta}$, it could either be that risk sharing is perfect but homogeneous preferences biased $\widehat{\theta}$ away from zero, or risk sharing is imperfect when preferences are heterogeneous but measurement errors of income biased the coefficient towards zero (Schulhofer-Wohl, 2011).

We use leisure as an instrument for income. Leisure tends to be negatively correlated with income, as people who work longer hours tend to have higher income. In addition, separability between leisure and consumption in preferences presumes that leisure is uncorrelated with consumption. Even if leisure is measured with error, as long as the error is uncorrelated with the measurement error of income, leisure is a valid instrument for income. If leisure and consumption are nonseparable, leisure may affect on consumption. Cochrane (1991) shows that if the social planner could freely transfer leisure across agents, an individual's leisure does not affect an individual's consumption allocation[24]. As such, we use contemporaneous leisure as an instrument for income.

[22] For detailed description of the two approaches, see Schulhofer-Wohl (2011).

[23] Detailed discussion of data can be found in Appendix A.

[24] However, if leisure is exogenously given and cannot be transferred, it has an effect on marginal utility of consumption and should be controlled on the right hand side of the estimation equation. In factor estimation, we did not include leisure as a control variable, because this leaves us with lagged leisure as an instrument for income, which makes the estimation procedure difficult to converge. Similar problems occur when Schulhofer-Wohl (2011) estimates risk sharing using U.S. household data.

Column (1) of Table 5 displays the estimated risk sharing coefficient $\widehat{\theta}$ when households are assumed to have common risk and time preferences. An estimate of 0.3125 indicates that a 1% increase in income would cause a 0.3% increase in food consumption when aggregate shock is controlled for. It is also statistically significant at the 5% level, as shown by the 95% bootstrap confidence intervals in the second row. Compared to the estimated risk sharing coefficient obtained by Schulhofer-Wohl (2011) for US households, which is 0.161 and is displayed at the bottom of Table 5, we observe that income changes have a smaller effect on consumption change for US households than for Chinese ones. This shows that the degree of risk sharing across household in China is lower than that across the U.S. if homogeneous preferences are assumed.

In Column (2), when risk preferences are allowed to be heterogeneous, the estimated $\widehat{\theta}$ becomes 0.2808, which is smaller than that in Column (1) for the homogeneous preferences specification. It is also statistically significant at the 5% level. However, this number is still higher than 0.129 for the U.S. households obtained by Schulhofer-Wohl (2011). Both the 90% and 95% bootstrap confidence intervals for the difference of the heterogeneous risk preferences specification from the homogeneous one include zero, indicating that the estimated risk sharing coefficient under heterogeneous risk preferences is not significantly different from that under homogeneous risk preferences. This result is different from that of the US in Schulhofer-Wohl (2011), which shows that the estimated risk sharing coefficient under risk preferences heterogeneity is significantly smaller than that under homogeneous risk preferences.

Furthermore, when only time preferences are assumed to be heterogeneous, the estimated $\widehat{\theta}$ is 0.6705 in Column (3) and significantly positively different from zero. It is also larger than that under the homogeneous preferences specification. This upward adjustment is consistent with the empirical results in Section 4.2. We find that incomes of people with less patience correlate more positively with the aggregate shock, which tends to bias downward the estimated risk sharing coefficient. However, the estimate is only marginally statistically significant at the 10% level. When comparing this number with the estimate for the US, which is at 0.105, we find that: 1). When only time preferences heterogeneity is allowed, the risk sharing coefficient for China is almost six times that of the US estimate. This produces a more diverging picture of degree of risk sharing at the household level in the two countries as compared to Column (1) and Column (2). 2). This enlarged difference comes from the fact that in China, for people with less patience their income correlates more positively with the aggregate shock, while in the US, the opposite is suggested by the results shown in Schulhofer-Wohl (2011). This is of some interest for China, although, statistically, 0.6705 is indifferent from 0.3125 based on the bootstrap confidence intervals for the difference with homogeneous preferences specification.

The last column displays the estimated risk sharing coefficient when both risk and time preferences are allowed to be heterogeneous among agents. The estimated $\widehat{\theta}$ is 0.0314, which is about one tenth of the estimated coefficient in Column (1) and statistically indifferent from zero. In addition, this difference between heterogeneous and homogeneous specifications is also statistically significant at the 10% and 5% levels, according to the bootstrapped confidence intervals shown in the fourth and fifth row of Column (4). As a result, we are able to reject the hypothesis that the homogeneous-preferences estimator is correctly specified. This result shows that after adjusting potential biases caused by neglecting heterogeneous risk and time preferences, Chinese households achieve full insurance during the mid 1990s to early 2010s.

Table 6 presents the results when we use the alternative measure of food consumption and household income. The results are qualitatively and quantitatively similar to that obtained in Table 5. The upper panel displays the results when consumption is measured using per adult equivalent food consumption when a small subset of food items are measured at the highest free market price[25]. The estimated $\widehat{\theta}$ for homogeneous preferences is 0.2814 and significantly different from zero at 5% level. When risk preferences are allowed to differ across households, this estimated coefficient reduces to 0.2720 and is significant at the 10% level. However, this reduction is not statistically significant at either 10% or 5%, as indicated by "no" in the second and third rows of Column (2). When only time preferences heterogeneity is allowed, the estimated $\widehat{\theta}$ is adjusted upward to 0.6099, which is significant at the 10% level. When risk and time preferences are present, the estimated risk sharing coefficient becomes 0.0026 and statistically indifferent from zero. In addition, the difference between this estimate of $\widehat{\theta}$ is significantly different from that in Column (1) under homogeneous specifications at the 10% level. Using an alternative measure of household income produces similar results in Row 4 of the upper panel. The middle panel shows the estimation results when consumption measure remains the same as in Table 5 while alternative income measure

[25]We have two measures of food expenditures at the household level, namely food consumption in which a small subset of vegetables and fruits are measured at the lowest free market price or the highest free market price. The discrepancies between these two measures are small, as can be seen from Table A1 in Appendix A.

is used[26]. The results are similar to those obtained in Table 5, which is reproduced in the bottom panel in Table 6. In addition, compared to the estimated risk sharing coefficients for US households, the results obtained in Table 6 show that neglecting preferences heterogeneity leads one to conclude that households in China have a lower degree of risk sharing than in the US. However, after the biases caused by preferences heterogeneity are adjusted, it turns out that Chinese households have full insurance that resembles their US counterparts.

Since food consumption is only a fraction of household nondurable consumption, estimation based on food consumption may produce a risk sharing estimate that serves as a lower bound of consumption insurance (Santaeulàlia-Llopis and Zheng, 2016; Blundell et al., 2008). Therefore we perform the estimation using the alternative consumption measure which, in addition to food consumption, also includes nondurable consumption available in CHNS. The estimation results are displayed in Table 7. The estimated risk sharing coefficient $\widehat{\theta}$ under four different specifications are 0.3889, 0.2993, 0.6829 and 0.0723 respectively, all of which are somewhat larger than the estimated $\widehat{\theta}$ in Table 5 when household consumption is measured by food expenditure. However, these discrepancies are small, and Table 7 yields the same conclusions we obtain in Table 5.

Results presented from Table 5 to Table 7 are based on household income that excludes transfer payments. CHNS records data from two broad channels through which households receive transfer payments. One is public transfer, mainly provided by government and work units. The other is private transfer, mainly among friends and relatives. Public transfer consists of welfare payments, health care, housing, pension, one-child subsidy, fuel and other government subsidies, plus food and other gifts from work units. Private transfer consists of payments and gift exchanges among friends and relatives. Since social and private insurance channels could potentially help improve risk sharing for households, we expect that by including transfer payments, the estimated risk sharing coefficient $\widehat{\theta}$ would be closer to zero compared to the case in which transfers are excluded.

Table 8 displays the estimation results when income is measured by using household income plus the sum of public and private transfers. The estimated results show that although the estimated $\widehat{\theta}$

[26]For those household members who work at collective/family farms and at the same time indicate they are also in charge of that farm, their income from farming may be double counted from wage income and agricultural income. As such for this group of people we either use wage income or agricultural income to account for their income from collective/family farms. This gives us two measures of household income.

is not closer to zero compared to that in Table 5 to 7, they now become less significantly different from zero. For example, the estimated $\widehat{\theta}$ in Column (2) and (3) now become insignificantly different from zero at either the 5% or 10% level, while they are significant at the 5% or 10% level in Table 5 to Table 7. The last column in Table 8 shows that, by including transfer into household income and taking into account heterogeneity in preferences, households in China enjoy full insurance against income fluctuations.

We further estimate the model using household income plus public transfer, or plus private transfer only, to investigate the effect of public and private transfer respectively. Results are presented in Table 9. The upper panel shows the results when only public transfers are added to household income. The lower panel presents the results when only private transfers are added to household income. In general, the results in both panels remain qualitatively and quantitatively similar to that in Table 8.

However, our results related to public and private transfer obtained above must be interpreted with a caveat. One issue is that CHNS does not provide tax information at household level. As such, we only obtain how much a household receives from the government, but do not know how much taxes it submitted. Another issue is that CHNS only provides how much households received from relatives and friends as transfers, but does not provide how much they transfer to them. If the amount they transfer out is negatively correlated with the amount they obtain, then the estimated risk sharing coefficient could be biased upward. In this case, the estimation we obtain in Table 8 and 9 could be considered as an upper bound of the risk sharing coefficient.

5.2. GMM estimation

We also use GMM estimation to estimate the risk sharing coefficient across households in China[27].

Table 10 presents the results of GMM estimation where household income and consumption are proxied by household adult equivalent income and food consumption, respectively.

Among the eight columns of Table 10, columns with odd numbers display results when leisure is used as an instrument for income only. Columns with even numbers display results when leisure is controlled for as an independent variable and used as an instrument for income and itself. This helps

[27] Detailed estimation technique can be found in Schulhofer-Wohl (2011).

us take into account the nonseparability between consumption and leisure. Column (1) shows the estimated risk sharing coefficient is 0.1846 and is insignificantly different from zero at the 5% level. This number is smaller than the estimated coefficient produced in Table 5 by factor estimation (0.3125). Columns (3) and (5) show that, when time or risk preferences are allowed to differ across households, the estimates become 0.6007 and 0.2353, respectively. Both are statistically significant at the 5% level. When both time and risk preferences are assumed to be heterogeneous among households, the estimated $\widehat{\theta}$ becomes 0.1424 and is statistically insignificantly different from zero. However, this number should be interpreted with caution. One reason is that we have taken quasi-difference of the second differences across the unevenly spaced waves in CHNS. Coupled with the fact that our data spans just six waves, this significantly reduces the available data points for regressions in Column (7) and (8). In addition, instruments are potentially weak, because their correlation with risk preferences need not be strong[28]. When leisure is controlled for as an independent variable, the effect on the estimated risk sharing coefficient varies across different specifications. It reduces the magnitude of the estimated $\widehat{\theta}$ when preferences are homogenous, or when only time preferences are heterogeneous. It increases the magnitude of the estimated $\widehat{\theta}$ when risk preferences are heterogeneous, or when time and risk preferences are heterogeneous. For all specifications except for Column (8), the overidentifying restrictions are never rejected[29].

The bottom row displays the corresponding estimation for the US households from Schulhofer-Wohl (2011). By comparison we find that the estimated risk sharing coefficients are smaller for Chinese households in Column (1), (2) and (5), while in Column (3), (4), (6), (7) and (8) the estimates are larger for Chinese households. By focusing on Column (1), (3) and (5), we observe that the estimated $\widehat{\theta}$ of Chinese households in Column (3) is larger than that in Column (1), indicating that, by allowing heterogeneous time preferences, $\widehat{\theta}$ is adjusted upward. This upward adjustment occurs because, in China, for less patient households their incomes correlate more positively with the aggregate shock. Second, the estimated $\widehat{\theta}$ of Chinese households in Column (5) is larger than that in Column (1), which is similar to the results from US households. In general, after taking into account time and risk preferences heterogeneity, columns (7) and (8) shows consistent results with

[28]Schulhofer-Wohl (2011) finds similar problems when risk preferences are allowed to differ across households in PSID data.

[29]In Column (8) in Table 10 and subsequent tables, because the model is just identified, overidentifying test p values are not available.

those obtained from factor estimation, that is, Chinese households have full insurance and this is similar to that of US households shown in Schulhofer-Wohl (2011).

When we use alternative household food consumption and income measures, the results remain qualitatively the same as presented in Table 10[30].

Table 11 presents the estimation results when household consumption is proxied by per adult equivalent household nondurable consumption, while the income measure remains unchanged. The results remain qualitatively similar compared to Table 10.

To gauge the effect of transfer income on household risk sharing, in Table 12 we use per adult equivalent household income plus transfer to proxy for household income. In general, including transfer into income produces similar results as compared to Table 10.

Table 13 displays the estimation results when transfer income is further split into public and private transfer. The upper panel presents results when income is proxied by household income plus public transfer, while the lower panel presents results when income is proxied by household income plus private transfer. The results remain qualitatively similar to that in Table 10 to Table 12.

In summary, the GMM estimation produces similar results as the factor model estimation.

5.3. The effect of institutional changes and labour market reforms

The previous estimation results show that, for households in China, standard risk sharing tests assuming homogeneous preferences across households produce a risk sharing coefficient that is biased upward when, in fact, preferences are heterogeneous. We argue that the reason this bias exists among households in China is because institutional changes and labour market reforms mentioned in Section 2 enable people to have more freedom in their occupational choices. As such, they can reveal their preferences more freely through their job choices, compared to before the 1990s, when the labour market in China was under strict restrictions, and institutional arrangements limited individuals' occupational choices. We use the Research Center on the Rural Economy (RCRE) Fixed Point Rural Household Survey in China to test this hypothesis. The survey started in 1986 and collects detailed household-level information on income, consumption and other household

[30] These results are not presented but are available upon request.

characteristics[31]. We use two subsamples of this survey, one from 1986 to 1991 and the other from 2003 to 2013[32]. The first sample was before the major institutional changes and labour market reforms took place. The reforms had taken place in the second sample. By comparing the estimated risk sharing coefficients from these two samples, we can test whether these reforms helped promote risk sharing across households in China by giving people more freedom in their occupational choices. Before 1991, when these reforms had not started, strict restrictions on labour markets in China prohibited people to have much freedom in their occupational choices. As a result, in our risk sharing test, whether heterogeneous preferences are taken into account or not should not have a significant effect on the estimated coefficients for the subsamples from 1986 to 1991. This is because, even if preferences are heterogeneous, people are forbidden to express their preferences through their job choices. Therefore, correlation between preferences and income variations cross-sectionally would be negligible and has no effect on estimated risk sharing coefficients from the standard risk sharing test. However, after 2003, when labour market reforms took place, people have more freedom to choose occupations according to their preferences, which introduces a potentially positive correlation between preferences and income variations that causes bias in the standard risk sharing test. Therefore, when we use the sample from 2003 to 2013, we should observe a significant difference between the estimated coefficient from the standard test and the test that takes into account heterogeneous preferences.

Table 14 presents the estimated results by using the RCRE sample from 1986 to 1991 and the factor estimation procedure[33]. Here household consumption is proxied by food consumption only. When using the standard risk sharing test assuming homogeneous preferences, we obtain an

[31]The complete RCRE survey covers more than 22,000 households in 300 villages in 31 provinces in China per survey year (Benjamin et al., 2011). By agreement, we have obtained access to data that is roughly one-tenth of the RCRE survey.

[32]Benjamin et al. (2005, 2011) provided detailed discussions of this dataset, we refer readers to them for more information. For detailed data compilation issues, please refer to Appendix A. The reason that the sample between 1992 and 2002 is not used is because information on hours worked at individual level is not provided during surveys in this period. As a result, we are not able to construct the instrumental variable leisure for household income. However, this does not have a major effect on our empirical investigation.

[33]Here we only use factor estimation. This is because factor estimation allows us to compare statistically the estimated coefficients under the standard test and the test with heterogeneous preferences, which is the key information in our reference.

estimated risk sharing coefficient at 0.3263, which is statistically significantly different from zero, and very close to the estimated coefficient we obtain in Table 5 using CHNS data. When taking into account heterogeneous preferences, we obtain an estimated coefficient of 0.2669, which is not statistically different from the coefficient under standard test at the 10% or 5% significant level. Table 15 shows that, when we use nondurable consumption rather than food consumption, the above results remain relatively unchanged. This shows that, for the RCRE sample from 1986 to 1991, whether heterogeneous preferences are being considered or not does not exert significant effect on the estimate risk sharing coefficient. This is consistent with our expectation, as people did not enjoy much freedom in revealing their preferences through job choices.

Table 16 shows the results by using the RCRE sample from 2003 to 2013 and household consumption is proxied by food consumption only. The first column shows that, under the standard risk sharing test with homogeneous preferences, the estimated coefficient is 0.3068 and significantly positively different from zero. However, when heterogeneous risk and time preferences are taken into account, the estimated risk sharing coefficient in column (4) becomes 0.2081 and is statistically significantly different from that in column (1) at the 10% significance level. When household nondurable consumption is used in place of household food consumption, the estimated results in Table 17 demonstrate an even stronger statistical difference between the standard test and tests that account for heterogeneous preferences. In Table 17, all estimated coefficients from column (2) to column (4) that, at least one preference heterogeneity is taken into account, are statistically significantly negative compared to that in column (1) at the 10% and 5% significance level. This shows that, for the RCRE sample from 2003 to 2013, preference heterogeneity causes significant positive bias in the standard risk sharing test, which tends to underestimate the degree of risk sharing across households. This is consistent with our expectation, as people in this latter sample period enjoyed more freedom in their occupational choices after the institutional changes and labour market reforms took place in China in the mid-1990s and early 2000s.

5.4. Summary and discussion

The above estimation results based on factor models show that allowing risk preferences heterogeneity tends to reduce the magnitude of the estimated risk sharing coefficient, while factor and GMM models show that allowing time preferences heterogeneity tends to increase it, based on CHNS data. When risk and time preferences are assumed to differ across households, factor and

GMM models produce an estimated $\widehat{\theta}$ that is insignificantly different from zero.

The differences in estimation results mainly come from two sources. First, factor and GMM models have different set-ups. The GMM test analyses how consumption responds to changes in income from one wave to the next, while the factor test analyses how consumption responds to deviations from income from its mean over time (Schulhofer-Wohl, 2011). Hall (1978) shows that, when households could only self-insure against income risks in the absence of relevant risk sharing arrangements, household consumption growth is uncorrelated with contemporaneous income growth. However, over the long time, household consumption would track household income more closely when risk sharing was incomplete (Hayashi et al., 1996). As a result, the factor model, due to its fixed effects transformation, may detect more failures of full risk sharing. That is why factor models produces at least as many significantly positive $\widehat{\theta}$s as GMM tests. Second, GMM tests allow us to control for leisure as a separate independent variable, while this is not possible in factor models.

Based on the CHNS data, both the factor model and GMM method produce estimates of the risk sharing coefficient that are insignificantly different from zero under heterogeneous risk and time preference specifications, indicative of full insurance at the household level in China. Compared to homogeneous preference specifications, the factor model shows that the difference between the "both heterogeneous" case and the "both homogeneous" case is statistically significant at the 5% or 10% level. Coupled with the institutional changes that occurred in China during the mid-1990s and early 2010s, it provides suggestive evidence that those reforms, particularly those labour market reforms which enabled people to have more freedom in their job choices, may have contributed to this increase of insurance from previous decades in which labour mobility and job choices were limited for rural and urban residents. In the 1980s or before, even if people had different preferences, there was not much freedom for them to reveal these differences through their job market choices. However, this is no more the case after the mid-1990s. As a result, when one performs the risk sharing test in China, it is more likely to generate biased estimates of risk sharing coefficients when one uses data after the mid-1990s. Furthermore, we use the longitudinal RCRE survey data at the household level in China to test the effect of these reforms on risk sharing at household level in China. We find that, for the RCRE sample from 1986 to 1991, whether preferences heterogeneity is accounted for or not does not produce any significant difference in the estimated risk sharing coefficients. However, for the RCRE sample from 2003 to 2013, neglecting preferences heterogeneity leads to an upward bias in the estimated risk sharing coefficient in the standard test. This indicates that reforms which give people more freedom of occupational choices so they can reveal their preferences through job selection promote risk sharing at the household level in China.

By comparing the estimated effects of income on consumption we obtained for households in China with US households in Schulhofer-Wohl (2011), we find that the degree of risk sharing across households in China based on CHNS data resembles that in the US when preferences heterogeneity is accounted for. However, the RCRE sample, which contains only rural households, produces an estimated risk sharing coefficient that indicates a lower degree of risk sharing compared to that based on CHNS data.

Our estimated risk sharing parameter could also be compared to a few papers that test risk sharing across China at different levels. We summarise them in Table 18. Most of them use aggregated provincial level data, and the point estimates of risk sharing coefficients have a wide range. Among them, Santaeulàlia-Llopis and Zheng (2016) is based on micro level household data, with which our results could be directly compared[34]. Their estimated risk sharing coefficients range between 0.041 and 0.108, which tend to be larger than our results in the factor model under the specification of risk and time preferences heterogeneity. This may be due to several reasons. First, they maintain the homogeneous preferences assumption in their test. We have shown that failure of accounting for risk preferences heterogeneity among Chinese households might cause an upward bias in the estimated risk sharing coefficient. Second, they did not deal with the potential measurement error problem in household income. Since it is likely that, in survey data, income might have been measured with error, this would cause a downward bias in the estimated risk sharing coefficient, which may explain why their estimated coefficients are smaller than ours under the standard test. Third, their data span is different from ours. Compared to our data, they used three more waves, 1989, 1991 and 1993 in CHNS, and they did not use the most recent 2011 wave.

However, our GMM estimates should also be interpreted with caution. Because the instruments we use are leisure, its differences and lags, when we control leisure as an explanatory variable, we need to assume that it is measured without error. In addition, it may suffer from weak instruments problem, because the correlation between preference heterogeneity and aggregate shock may be weak.

[34]Santaeulàlia-Llopis and Zheng (2016) perform the full insurance test in their online appendix, which is available at http://r-santaeulalia.net/pdfs/The-Price-of-Growth-Appendix.pdf.

6. Conclusion

In this paper we conduct tests of complete consumption risk sharing across households in China from 1997 to 2011. Standard risk sharing tests often assume preferences are homogeneous across agents. However, failure to account for preferences heterogeneity may cause biases in the estimated risk sharing coefficient. To be more specific, neglecting risk preferences heterogeneity tends to bias the risk sharing parameter upward because people with less risk aversion may choose occupations that bear more aggregate risk of the economy. In addition, neglecting time preferences heterogeneity may bias the risk sharing parameter upward or downward, depending on whether people with more patience bear more or less of the aggregate risk of the economy. Furthermore, for households in China, institutional arrangements may affect whether households can express their preferences through their occupational choices, which offers us an opportunity to evaluate the effect of these institutional arrangements on household risk sharing in China.

By using two household-level survey datasets, China Health and Nutrition Survey (CHNS) and China Family Panel Studies (CFPS), we first show empirically that in China, less risk-averse households bear more aggregate risk through a more positive correlation between their income and the aggregate shock of the economy. In addition, we also show that less-patient Chinese households bear more aggregate risk through a more positive correlation between their income and the aggregate shock. This freedom of job choices was made available to individuals through a series of institutional reforms that occurred during the mid-1990s and early 2000s.

We further use CHNS datasets with six waves (1997, 2000, 2004, 2006, 2009, 2011) to empirically test the degree of risk sharing across households in China. We find that neglecting preferences heterogeneity leads to an overestimate of the risk sharing parameter which underestimates the degree of risk sharing across households. By incorporating preferences heterogeneity, households in China enjoy a level of risk sharing that is similar to that across US households. We then use RCRE survey data to show that this improvement of risk sharing from homogeneous to heterogeneous preferences comes from the institutional reforms implemented in China during the mid-1990s to early 2010s, which gave Chinese people more freedom in their labour market choices so they could more freely sort themselves into different occupations according to their preferences.

Reference

Ahn, S. C., Lee, Y. H., Schmidt, P., 2001. GMM estimation of linear panel data models with time-varying individual effects. *Journal of Econometrics* 101 (2), 219 – 255.

Anderhub, V., Güth, W., Gneezy, U., Sonsino, D., 2001. On the interaction of risk and time preferences: An experimental study. *German Economic Review* 2 (3), 239–253.

Anderson, L. R., Mellor, J. M., 2008. Predicting health behaviors with an experimental measure of risk preference. *Journal of Health Economics* 27 (5), 1260–1274.

Barsky, R. B., Juster, F. T., Kimball, M. S., Shapiro, M. D., 1997. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Quarterly Journal of Economics* 112 (2), 537–579.

Becker, G. M., DeGroot, M. H., Marschak, J., 1964. Measuring utility by a single-response sequential method. *Behavioral Science* 9 (3), 226–232.

Becker, G. S., Mulligan, C. B., 1997. The endogenous determination of time preference. The *Quarterly Journal of Economics* 112 (3), 729–758.

Benjamin, D., Brandt, L., Giles, J., July 2005. The Evolution of Income Inequality in Rural China. *Economic Development and Cultural Change* 53 (4), 769–824.

Benjamin, D., Brandt, L., Giles, J., December 2011. Did Higher Inequality Impede Growth in Rural China? *Economic Journal* 121 (557), 1281–1309.

Blundell, R., Low, H., Preston, I., 2013. Decomposing changes in income risk using consumption data. *Quantitative Economics* 4 (1), 1–37.

Blundell, R., Pistaferri, L., Preston, I., 2008. Consumption inequality and partial insurance. *American Economic Review* 98 (5), 1887–1921.

Bonin, H., Dohmen, T., Falk, A., Huffman, D., Sunde, U., 2007. Cross-sectional earnings risk and occupational sorting: The role of risk attitudes. *Labour Economics* 14 (6), 926 – 937, education and RiskEducation and Risk S.I.

Chamon, M., Liu, K., Prasad, E., 2013. Income uncertainty and household savings in china. *Journal of Development Economics* 105, 164 – 177.

Chan, K. S., Lai, J. T., Yan, I. K. M., 2014. Consumption risk sharing and self-insurance across provinces in China: 1952-2008. *China Economic Review* 30 (C), 66–85.

Chiappori, P.-A., Samphantharak, K., Schulhofer-Wohl, S., Townsend, R. M., 2014. Heterogeneity and risk sharing in village economies. *Quantitative Economics* 5 (1), 1–27.

Choi, H., Lugauer, S., Mark, N. C., 2014. Precautionary saving of chinese and u.s. households. NBER Working Papers 20527, National Bureau of Economic Research, Inc.

Chow, G. C., May 2004. Economic Reform and Growth in China. *Annals of Economics and Finance* 5 (1), 127–152.

Cochrane, J. H., 1991. A simple test of consumption insurance. *Journal of Political Economy* 99 (5), 957–76.

Curtis, C. C., Mark, N., 2010. Business cycles, consumption and risk-sharing: How different is china? NBER Working Papers 16154, National Bureau of Economic Research, Inc.

Cutler, D. M., Finkelstein, A., McGarry, K., 2008. Preference heterogeneity and insurance markets: Explaining a puzzle of insurance. *American Economic Review* 98 (2), 157–62.

Deaton, A., 1992. Understanding Consumption. Clarendon Press, Oxford.

Dong, K., 2009. Medical insurance system evolution in china. *China Economic Review* 20 (4), 591 – 597, symposium on Health Economics Issues in ChinaHealth Symposium.

Du, J., He, Q., Rui, O. M., 2011. Channels of interprovincial risk sharing in china. *Journal of Comparative Economics* 39 (3), 383–405.

Fuchs, V., 1982. Time preference and health: An exploratory study. In: Economic Aspects of Health. National Bureau of Economic Research, Inc, pp. 93–120.

Fuchs-Schündeln, N., Schündeln, M., 2005. Precautionary savings and self-selection: Evidence from the german reunification "experiment". *The Quarterly Journal of Economics* 120 (3), 1085–1120.

Giles, J., Park, A., Cai, F., 2006. How has economic restructuring affected China's urban workers? *China Quarterly* 185, 61–95.

Guiso, L., Paiella, M., 2008. Risk aversion, wealth, and background risk. *Journal of the European Economic Association* 6 (6), 1109–1150.

Hall, R. E., 1978. Stochastic Implications of the Life Cycle-Permanent Income Hypothesis: Theory and Evidence. *Journal of Political Economy* 86 (6), 971–87.

Hayashi, F., Altonji, J., Kotlikoff, L., 1996. Risk-sharing between and within families. *Econometrica* 64 (2), 261–294.

Heathcote, J., Storesletten, K., Violante, G. L., 2008. Insurance and opportunities: A welfare analysis of labor market risk. *Journal of Monetary Economics* 55 (3), 501 – 525.

Ho, C.-Y., Ho, W.-Y. A., Li, D., 2010. Consumption Fluctuations and Welfare: Evidence from China. *World Development* 38 (9), 1315–1327.

Ho, C.-Y., Ho, W.-Y. A., Li, D., 2015. Intranational risk sharing and its determinants. *Journal of International Money and Finance* 51 (C), 89–113.

Huang, Y., January 2008. Capitalism with Chinese Characteristics. No. 9780521898102 in Cambridge Books. Cambridge University Press.

Iyer, L., Meng, X., Qian, N., Zhao, X., Dec. 2013. Economic Transition and Private-Sector Labor Demand: Evidence from Urban China. NBER Working Papers 19733, National Bureau of Economic Research, Inc.

Jamison, J., Karlan, D., Zinman, J., 2012. Measuring risk and time preferences and their connections with behavior. Tech. rep., Federal Reserve Bank of Boston.

Krueger, D., Perri, F., 2006. Does income inequality lead to consumption inequality? evidence and theory. *The Review of Economic Studies* 73 (1), 163–193.

Lai, J. T., So, E. P. K., Yan, I. K. M., 2014. Intergovernmental Fiscal Arrangements and Provincial Consumption Risk Sharing in China. *Emerging Markets Finance and Trade* 50 (3), 45–58.

Lusk, J. L., Coble, K. H., 2005. Risk Perceptions, Risk Preference, and Acceptance of Risky Food. *American Journal of Agricultural Economics* 87 (2), 393–405.

Mace, B. J., 1991. Full insurance in the presence of aggregate uncertainty. *Journal of Political Economy* 99 (5), 928–56.

Mazzocco, M., Saini, S., 2012. Testing efficient risk sharing with heterogeneous risk preferences. *American Economic Review* 102 (1), 428–68.

Meng, X., 2003. Unemployment, consumption smoothing, and precautionary saving in urban china. *Journal of Comparative Economics* 31 (3), 465–485.

Meng, X., Fall 2012. Labor Market Outcomes and Reforms in China. *Journal of Economic Perspectives* 26 (4), 75–102.

Morduch, J., Summer 1995. Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives* 9 (3), 103–114.

OECD, 2011. Divided we stand: Why inequality keeps rising. Tech. rep., Organisation for Economic Co-operation and Development.

Rickne, J., 2013. Labor market conditions and social insurance in china. *China Economic Review* 27, 52 – 68.

Santaeulàlia-Llopis, R., Zheng, Y., 2016. The price of growth: Consumption insurance in china 1989-2009. working paper, City University of Hong Kong.

Schulhofer-Wohl, S., 2011. Heterogeneity and Tests of Risk Sharing. *Journal of Political Economy* 119 (5), 925 – 958.

Storesletten, K., Zilibotti, F., 08 2014. Chinas Great Convergence and Beyond. *Annual Review of Economics* 6 (1), 333–362.

Sutter, M., Kocher, M. G., Glätzle-Rüetzler, D., Trautmann, S. T., 2013. Impatience and uncertainty: Experimental decisions predict adolescents' field behavior. *American Economic Review* 103 (1), 510–31.

Townsend, R. M., 1994. Risk and insurance in village india. *Econometrica* 62 (3), 539–91.

Voors, M. J., Nillesen, E. E. M., Verwimp, P., Bulte, E. H., Lensink, R., Van Soest, D. P., 2012. Violent conflict and behavior: A field experiment in burundi. *American Economic Review* 102 (2), 941–64.

Wolbert, E., Riedl, A., 2013. Measuring Time and Risk Preferences: Realiability, Stability, Domain Specificity. CESifo Working Paper Series 4339, CESifo Group Munich.

Xu, X., 2008. Consumption risk-sharing in china. *Economica* 75 (298), 326–341.

Yang, Y., 1999. China Food Composition. Beijing Medical University Press.

Yang, Y., 2004. China Food Composition. Beijing Medical University Press.

Yang, Y., 2009. China Food Composition. Beijing Medical University Press.

Yang, Y., Wang, G., Pan, X., 2002. China Food Composition. Beijing Medical University Press.

Zhao, Z., 2003. Rural-urban migration in china c what do we know and what do we need to know? Tech. rep., China Center for Economic Research, Peking University.

Zhu, X., 2012. Understanding china's growth: Past, present, and future. *Journal of Economic Perspectives* 26 (4), 103–24.

Table 1: Regressions of log(real annual adult equivalent household income) on aggregate shock (log per capita real GDP) and risk preference (CHNS)

	OLS	FE	RE
Panel A: Risk preferences proxied by smoking[a]			
smoke(α_1)	-0.4324***	-0.2654***	-0.3394***
	(0.0604)	(0.0777)	(0.0703)
aggshock(α_2)	0.7393***	0.7899***	0.7814***
	(0.0366)	(0.0695)	(0.0505)
smoke * aggshock(α_3)	0.3269***	0.2075**	0.2592***
	(0.0524)	(0.0649)	(0.0594)
control variables	yes	yes	yes
N	10236	10236	10236
Panel B: Risk preferences proxied by drinking[a]			
drink(α_1)	-0.4527***	-0.2966***	-0.3626***
	(0.0602)	(0.0837)	(0.0750)
aggshock(α_2)	0.6946***	0.7572***	0.7447***
	(0.0379)	(0.0717)	(0.0487)
drink * aggshock(α_3)	0.4101***	0.2495***	0.3218***
	(0.0519)	(0.0682)	(0.0612)
control variables	yes	yes	yes
N	10196	10196	10196
Panel C: Risk preferences proxied by use of preventive health care services[a]			
prvhcare(α_1)	0.4009	0.0832	0.2539
	(0.2616)	(0.1966)	(0.2105)
aggshock(α_2)	0.8667***	0.8400***	0.8677***
	(0.0284)	(0.0689)	(0.0458)
prvhcare * aggshock(α_3)	-0.1709	-0.1067	-0.1474
	(0.1978)	(0.1634)	(0.1678)
control variables	yes	yes	yes
N	10582	10582	10582

[a] Data used here was collected from 1997, 2000, 2004, 2006, 2009 and 2011 waves of China Health and Nutrition Survey (CHNS). SMOKE indicates whether or not household's head smokes; DRINK indicates whether or not household's head drinks; PRVHCARE indicates whether or not household's head used preventive health service during the last four weeks at the time of interview.

[b] Standard errors in parentheses.

[c] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[d] Control variables include household head's age, gender, marital status, ethnicity, years of education, occupation type, whether a cadre, whether with urban registration, family dependence ratio, plus a constant. The estimated coefficients are not shown here but are available upon request.

Table 2: Regressions of log(real annual adult equivalent household income) on aggregate variables (log per capita real consumption) and risk preference

	OLS	FE	RE
Panel A: Risk preferences proxied by smoking			
smoke(α_1)	-0.1504***	-0.0911**	-0.1180***
	(0.0240)	(0.0291)	(0.0259)
aggshock(α_2)	0.9962***	1.0800***	1.0496***
	(0.0484)	(0.0904)	(0.0667)
smoke * aggshock(α_3)	0.4348***	0.2880**	0.3503***
	(0.0696)	(0.0871)	(0.0800)
control variables	yes	yes	yes
N	10236	10236	10236
Panel B: Risk preferences proxied by drinking[a]			
drink(α_1)	-0.0993***	-0.0859**	-0.0875**
	(0.0239)	(0.0320)	(0.0294)
aggshock(α_2)	0.9335***	1.0348***	0.9976***
	(0.0502)	(0.0927)	(0.0640)
drink * aggshock(α_3)	0.5531***	0.3504***	0.4405***
	(0.0690)	(0.0914)	(0.0822)
control variables	yes	yes	yes
N	10196	10196	10196
Panel C: Risk preferences proxied by use of preventive health care services[a]			
prvhcare(α_1)	0.2579*	0.0120	0.1374
	(0.1021)	(0.0707)	(0.0783)
aggshock(α_2)	1.1801***	1.2228***	1.1900***
	(0.0379)	(0.0867)	(0.0606)
prvhcare * aggshock(α_3)	-0.2492	-0.2159	-0.2411
	(0.2555)	(0.2088)	(0.2104)
control variables	yes	yes	yes
N	10582	10582	10582

Please refer to notes in Table 1.

Table 3: Regressions of log(real per capita household income) on aggregate variables (per capita real GDP) and time preference

	OLS	FE	RE
Panel A: Time preferences proxied by self-rated health[a]			
self-rated health (κ_1)	1.1273	-0.1087	0.7128
	(0.7148)	(0.7895)	(0.7920)
aggshock (κ_2)	4.1423***	5.7933**	3.7122***
	(0.5717)	(1.9043)	(0.7693)
self-rated health * aggshock (κ_3)	-0.2710	0.0194	-0.1747
	(0.1645)	(0.1818)	(0.1828)
control variables	yes	yes	yes
N	13062	13062	13062
Panel B: Time preferences proxied by household total assets			
total assets (κ_1)	0.0159	0.0724**	0.0297*
	(0.0137)	(0.0252)	(0.0151)
aggshock (κ_2)	2.9955***	6.1493***	3.0055***
	(0.2748)	(1.8050)	(0.4782)
total assets * aggshock (κ_3)	-0.0030	-0.0161**	-0.0062
	(0.0031)	(0.0057)	(0.0034)
control variables	yes	yes	yes
N	12730	12730	12730

[a] Data used here was collected from the 2010 and 2012 waves of China Family Panel Survey (CFPS).Self-rated health denotes the self-evaluation of overall health of household head; Total assets denotes household's total assets (net of debt).

[b] Standard errors in parentheses.

[c] * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

[d] Control variables include household head's age, gender, years of education, ethnicity, marital status, whether a communist party member, whether with urban registration, family size, plus a constant. The estimated coefficients are not shown here but are available upon request.

Table 4: Regressions of log(real per capita household income1) on aggregate variables (per capita real personal consumption) and time preference

	OLS	FE	RE
Panel 1: Time preferences proxied by self-rated health			
self-rated health (κ_1)	1.3029	-0.1213	0.8260
	(0.8213)	(0.9073)	(0.9104)
aggshockc2 (κ_2)	5.3033***	7.4171**	4.7527***
	(0.7319)	(2.4380)	(0.9849)
self-rated health*aggshock (κ_3)	-0.3470	0.0249	-0.2237
	(0.2106)	(0.2327)	(0.2340)
control variables	yes	yes	yes
N	13062	13062	13062
Panel 2: Time preferences proxied by household total asset			
total asset (κ_1)	0.0178	0.0829**	0.0337
	(0.0157)	(0.0289)	(0.0173)
aggshockc2 (κ_2)	3.8351***	7.8729***	3.8479***
	(0.3519)	(2.3109)	(0.6122)
total asset*aggshock (κ_3)	-0.0038	-0.0207**	-0.0080
	(0.0040)	(0.0073)	(0.0043)
control variables	yes	yes	yes
N	12730	12730	12730

Please refer to notes in Table 3.

Table 5: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income[b])

Estimated risk sharing coefficient $\widehat{\theta}$	log(food consumption per adult equivalent)			
	(1)	(2)	(3)	(4)
log(income)	**0.3125****	**0.2808****	**0.6705***	**0.0314**
90% confidence interval	(0.1403, 0.4855)	(0.0679, 0.5761)	(0.1233, 1.1418)	(-0.3111, 0.2782)
95% confidence interval	(0.0861, 0.5333)	(0.0066, 0.6499)	(-0.1267, 1.2222)	(-0.3901, 0.3421)
90% confidence interval for difference from homogeneous preferences	-	(-0.1549, 0.1702)	(-0.1041, 0.7184)	**(-0.5783**, **-0.0289)**
95% confidence interval for difference from homogeneous preferences	-	(-0.1703, 0.1857)	(-0.2763, 0.7872)	**(-0.6403**, **-0.0068)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	**0.161**	**0.129**	**0.105**	**0.092**

a. Household per adult equivalent food consumption is computed using free market prices (lowest).

b. Household per adult equivalent income is household wage income, income from agriculture, business and capital. Transfer income, either from public channel or private channel, is excluded.

c. ** and * indicate 5% and 10% significance level, respectively.

d. As comparable to SW (2011), equal-tailed 95% confidence intervals are computed using 79 bootstrap samples. The bootstrap samples are constructed by drawing Primary Sampling Units with replacement in each wave to allow correlation across households in each PSU. Because CHNS has significantly fewer waves than PSID and higher attrition rate than PSID, we are unable to perform bootstrap sampling by drawing PSUs with replacement from the original sample to allow for correlation over time among households.

Table 6: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income[b])

Estimated risk sharing coefficient $\widehat{\theta}$	log(food consumption per adult equivalent measured at free market price highest)			
	(1)	(2)	(3)	(4)
log(income)	**0.2814**[c]**	**0.2720***	**0.6099***	**0.0026**
different from homogeneous estimate at 10% significance level[d]?	-	no	no	no
different from homogeneous estimate at 5% significance level?	-	no	no	no
log(alternative income measure)	**0.2818****	**0.2716***	**0.6108***	**0.0026**
different from homogeneous estimate at 10% significance level?	-	no	no	**yes**
different from homogeneous estimate at 5% significance level?	-	no	no	no
Estimated risk sharing coefficient $\widehat{\theta}$	**log(food consumption per adult equivalent measured at free market price lowest)**			
	(1)	(2)	(3)	(4)
log(alternative income measure)	**0.3129****	**0.2805****	**0.6714***	**0.0316**
different from homogeneous estimate at 10% significance level?	-	no	no	**yes**
different from homogeneous estimate at 5% significance level?	-	no	no	**yes**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ from Table 5	**0.3125****	**0.2808****	**0.6705***	**0.0314**
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	**0.161**	**0.129**	**0.105**	**0.092**

a. Alternative household per adult equivalent food consumptions are used for regression.

b. Alternative household per adult equivalent income, excluding transfer, are used for regression.

c. ** and * indicate 5% and 10% significance level, respectively.

d. Bootstrap confidence intervals are constructed at 10% and 5% level by using 79 bootstrap samples. Instead of directly displaying the confidence intervals, we opt for just showing if the estimated risk sharing coefficient under heterogeneous risk preferences is significantly different from homogeneous estimate at 10% or 5% significance level.

Table 7: Regressions of log(per adult equivalent household nondurable consumption[a]) on log(per adult equivalent household income[b])

Estimated risk sharing coefficient $\widehat{\theta}$	log(food consumption per adult equivalent)			
	(1)	(2)	(3)	(4)
log(income)	**0.3889****	**0.2993***	**0.6829***	**0.0723**
90% confidence interval	(0.1916, 0.5884)	(0.1095, 0.5231)	(0.0434, 1.0665)	(-0.3426, 0.3184)
95% confidence interval	(0.1320, 0.6283)	(-0.0064, 0.6069)	(-0.1096, 1.1809)	(-0.5798, 0.4357)
90% confidence interval for difference from homogeneous preferences	-	(-0.2057, 0.0806)	(-0.1319, 0.5862)	**(-0.7572**, **-0.0937)**
95% confidence interval for difference from homogeneous preferences	-	(-0.2187, 0.1209)	(-0.3436, 0.6351)	**(-0.8139**, **-0.0457)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes

a. Household per adult equivalent nondurable consumption is computed using household food consumption plus other nondurable consumption.

b. Household per adult equivalent income is household wage income, income from agriculture, business and capital. Transfer income, either from public channel or private channel, is excluded.

c. ** and * indicate 5% and 10% significance level, respectively.

d. As comparable to SW (2011), equal-tailed 95% confidence intervals are computed using 79 bootstrap samples. The bootstrap samples are constructed by drawing Primary Sampling Units with replacement in each wave to allow correlation across households in each PSU. Because CHNS has significantly fewer waves than PSID and higher attrition rate than PSID, we are unable to perform bootstrap sampling by drawing PSUs with replacement from the original sample to allow for correlation over time among households.

Table 8: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income plus transfer[b])

Estimated risk sharing coefficient $\widehat{\theta}$	log(food consumption per adult equivalent)			
	(1)	(2)	(3)	(4)
log(income plus transfers)	**0.4346****	**0.3818**	**1.0044**	**0.0525**
90% confidence interval	(0.1650, 0.6700)	(-0.0606, 0.7036)	(-1.3216, 1.7468)	(-0.4264, 0.3395)
95% confidence interval	(0.1360, 0.7279)	(-1.0071, 0.8295)	(-2.7184, 1.9206)	(-0.4851, 0.5081)
90% confidence interval for difference from homogeneous preferences	-	(-0.3059, 0.1738)	(-1.4623, 1.1676)	**(-0.7649, -0.0296)**
95% confidence interval for difference from homogeneous preferences	-	(-1.1770, 0.2703)	(-2.8882, 1.3920)	(-0.9133, 0.0061)
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes

a. Household per adult equivalent food consumption is computed using the lowest free market prices for a small group of food items.

b. Household per adult equivalent income is household wage income, income from agriculture, business and capital, **plus transfer payments from both public and private channels**.

c. ** and * indicate 5% and 10% significance level, respectively.

d. As comparable to SW (2011), equal-tailed 95% confidence intervals are computed using 79 bootstrap samples. The bootstrap samples are constructed by drawing Primary Sampling Units with replacement in each wave to allow correlation across households in each PSU. Because CHNS has significantly fewer waves than PSID and higher attrition rate than PSID, we are unable to perform bootstrap sampling by drawing PSUs with replacement from the original sample to allow for correlation over time among households.

d. ** and * indicate 5% and 10% significance level, respectively.

Table 9: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income plus either public or private transfer[b])

Estimated risk sharing coefficient $\widehat{\theta}$	log(food consumption per adult equivalent)			
	(1)	(2)	(3)	(4)
log(income plus public transfers)	**0.3697****	**0.3185****	**0.6752**	**0.0936**
90% confidence interval	(0.1423, 0.5541)	(0.1382, 0.5826)	(-0.2757, 1.1355)	(-0.1935, 0.3334)
95% confidence interval	(0.0758, 0.5966)	(0.0596, 0.6839)	(-0.3709, 1.2759)	(-0.2501, 0.3831)
90% confidence interval for difference from homogeneous preferences	-	(-0.1908, 0.1536)	(-0.4362, 0.6717)	**(-0.5552, -0.0413)**
95% confidence interval for difference from homogeneous preferences	-	(-0.2138, 0.1871)	(-0.7502, 0.6889)	(-0.5878, 0.0623)
log(income plus private transfers)	**0.4213****	**0.3502****	**0.8662***	**0.0789**
90% confidence interval	(0.1739, 0.6621)	(0.0816, 0.6369)	(0.0047, 1.4170)	(-0.3293, 0.3209)
95% confidence interval	(0.1523, 0.7104)	(0.0008, 0.7741)	(-0.3547, 1.5549)	(-0.6116, 0.3382)
90% confidence interval for difference from homogeneous preferences	-	(-0.2822, 0.1233)	(-0.3703, 0.8931)	**(-0.6904, -0.0683)**
95% confidence interval for difference from homogeneous preferences	-	(-0.3743, 0.1680)	(-0.7923, 0.9090)	**(-0.9486, -0.0488)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes

a. Household per adult equivalent food consumption is computed using the lowest free market prices for a small group of food items.

b. Household per adult equivalent income is household wage income, income from agriculture, business and capital, **plus transfer income from either public or private channels**.

c. ** and * indicate 5% and 10% significance level, respectively.

d. As comparable to SW (2011), equal-tailed 95% confidence intervals are computed using 79 bootstrap samples. The bootstrap samples are constructed by drawing Primary Sampling Units with replacement in each wave to allow correlation across households in each PSU. Because CHNS has significantly fewer waves than PSID and higher attrition rate than PSID, we are unable to perform bootstrap sampling by drawing PSUs with replacement from the original sample to allow for correlation over time among households.

Table 10: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income[b]), GMM estimates

	log(food consumption per adult equivalent)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(income)	**0.1846**	**-0.0924**	**0.6007****	**0.0460**	**0.2353*****	**0.2671****	**0.1424**	**0.6637**
	(0.1136)[a]	(0.2074)	(0.2152)	(0.3597)	(0.0854)	(0.1248)	(1.0258)	(0.8627)
log(leisure)	.	-0.1798***	.	-0.0838***	.	0.0470***	.	0.3081
	.	(0.0142)	.	(0.0146)	.	(0.0044)	.	(0.4065)
Test of overidentifying restrictions :								
χ^2	5.9847	3.3488	1.5209	2.1821	3.4772	3.4805	0.1249	0.0152
d.f.	6	5	5	4	7	6	1	0
p	0.4249	0.6464	0.9107	0.7023	0.8377	0.7466	0.7238	.
Heterogeneity:								
risk aversion	no	no	no	no	yes	yes	yes	yes
time preference	no	no	yes	yes	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	0.283	0.234	-0.001	-0.013	0.345	0.123	0.053	-0.086

[a] Estimated coefficients are followed by standard errors.

[b] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Regressions of log(per adult equivalent household nondurable consumption^a) on log(per adult equivalent household income^b), GMM estimates

	log(nondurable consumption per adult equivalent)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(income)	**0.2565****	**-0.0011**	**0.6888****	**0.3332**	**0.2194****	**0.0640**	**3.7384**	**0.9018****
	(0.1128)[a]	(0.1966)	(0.2414)	(0.4587)	(0.0891)	(0.3379)	(11.4118)	(0.3832)
log(leisure)	.	-0.1670***	.	-0.1704***	.	0.0139	.	0.2173
	.	(0.0130)	.	(0.0241)	.	(0.0183)	.	(1.3869)
Test of overidentifying restrictions :								
χ^2	5.8363	4.0368	2.1894	2.0868	6.1023	1.5992	0.0579	0.1541
d.f.	6	5	5	4	7	6	1	0
p	0.4418	0.5441	0.8224	0.7198	0.5279	0.9526	0.8098	
Heterogeneity:								
risk aversion	no	no	no	no	yes	yes	yes	yes
time preference	no	no	yes	yes	no	no	yes	yes

[a] Estimated coefficients are followed by standard errors.

[b] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income plus transfer[b]), GMM estimates

	log(food consumption per adult equivalent)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(income)	**0.2103**	**-0.0596**	**0.3907***	**0.0839**	**0.2959****	**0.2722**	**-4.9368**	**0.5961**
	(0.1468)[a]	(0.2662)	(0.1960)	(0.2349)	(0.1146)	(0.1495)	(6.5045)	(1.0680)
log(leisure)	.	-0.1399***	.	-0.0389	.	-0.0001	.	0.1510
	.	(0.0154)	.	(0.0130)	.	(0.0042)	.	(0.2329)
Test of overidentifying restrictions :								
χ^2	4.9906	3.5172	4.4043	0.9950	1.4815	1.9374	0.2976	0.0046
d.f.	6	5	5	4	7	6	1	0
p	0.5450	0.6208	0.4928	0.9106	0.9829	0.9254	0.5854	.
Heterogeneity:								
risk aversion	no	no	no	no	yes	yes	yes	yes
time preference	no	no	yes	yes	no	no	yes	yes

[a] Estimated coefficients are followed by standard errors.

[b] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Regressions of log(per adult equivalent household food consumption[a]) on log(per adult equivalent household income plus either public transfer or private transfer[b]), GMM estimates

	log(food consumption per adult equivalent)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(income+public transfer)	**0.2480***	**-0.0908**	**0.3910****	**-0.0020**	**0.1600**	**0.2027**	**0.0126**	**2.4137**
	(0.1307)[a]	(0.2547)	(0.1770)	(0.2789)	(0.1505)	(0.1318)	(1.0074)	(3.0716)
log(leisure)	.	-0.1880***	.	-0.0921***	.	-0.0192***	.	-0.5652
	.	(0.0172)	.	(0.0125)	.	(0.0053)	.	(1.2661)
Test of overidentifying restrictions :								
χ^2	6.7574	4.4221	3.9670	1.7977	2.9434	3.0607	1.2847	0.2315
d.f.	6	5	5	4	7	6	1	0
p	0.3439	0.4904	0.5542	0.7729	0.8902	0.8012	0.2570	.
	log(food consumption per adult equivalent)							
log(income+private transfer)	**0.2203**	**-0.1511**	**0.6839****	**0.1710**	**0.2810****	**0.1951**	**-0.3192**	**0.5412**
	(0.1440)[a]	(0.2873)	(0.2694)	(0.4608)	(0.1110)	(0.1630)	(0.2594)	(1.0727)
log(leisure)	.	-0.1910***	.	-0.0401**	.	-0.0227***	.	0.3102***
	.	(0.0181)	.	(0.0181)	.	(0.0046)	.	(0.0412)
Test of overidentifying restrictions :								
χ^2	5.5926	2.8858	1.4031	1.5758	3.1718	3.8691	0.00004	0.0412
d.f.	6	5	5	4	7	6	1	0
p	0.4703	0.7175	0.9240	0.8131	0.8687	0.6944	0.9948	.
Heterogeneity:								
risk aversion	no	no	no	no	yes	yes	yes	yes
time preference	no	no	yes	yes	no	no	yes	yes

[a] Estimated coefficients are followed by standard errors.

[b] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: Regressions of log(household food consumption) on log(household income) using the RCRE sample from 1986 to 1991[a]

Estimated risk sharing coefficient $\widehat{\theta}$	log(household food consumption)			
	(1)	(2)	(3)	(4)
log(income)	**0.3263****	**0.3256****	**0.3132****	**0.2669****
90% confidence interval	(0.2350, 0.4513)	(0.2378, 0.4257)	(0.2026, 0.4064)	(0.1366, 0.3708)
95% confidence interval	(0.2178, 0.4667)	(0.2245, 0.4360)	(0.1724, 0.4185)	(0.1335, 0.4097)
90% confidence interval for difference from homogeneous preferences	-	(-0.0757, 0.0965)	(-0.0926, 0.0542)	**(-0.1702, 0.0543)**
95% confidence interval for difference from homogeneous preferences	-	(-0.0818, 0.1330)	(-0.1254, 0.0645)	**(-0.1936, 0.0951)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	**0.161**	**0.129**	**0.105**	**0.092**

[a] Estimated coefficients are followed by standard errors.

[b] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Regressions of log(household nondurable consumption) on log(household income) using the RCRE sample from 1986 to 1991[a]

Estimated risk sharing coefficient $\widehat{\theta}$	log(household nondurable consumption)			
	(1)	(2)	(3)	(4)
log(income)	**0.3674****	**0.3428****	**0.3352****	**0.3205****
90% confidence interval	(0.2766, 0.4637)	(0.2722, 0.4304)	(0.2259, 0.4189)	(0.1941, 0.4789)
95% confidence interval	(0.2582, 0.4914)	(0.2469, 0.4683)	(0.1949, 0.4432)	(0.1873, 0.5097)
90% confidence interval for difference from homogeneous preferences	-	(-0.0951, 0.0601)	(-0.0990, 0.0207)	(**-0.1724**, **0.1150)**
95% confidence interval for difference from homogeneous preferences	-	(-0.1011, 0.0978)	(-0.1359, 0.0336)	(**-0.1859**, **0.1364)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	**0.161**	**0.129**	**0.105**	**0.092**

[a] Estimated coefficients are followed by standard errors.

[b] * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Regressions of log(household food consumption) on log(household income) using the RCRE sample from 2003 to 2013

Estimated risk sharing coefficient $\widehat{\theta}$	log(household food consumption)			
	(1)	(2)	(3)	(4)
log(income)	**0.3068****	**0.2448***	**0.2371****	**0.2081****
90% confidence interval	(0.1803, 0.4120)	(0.0666, 0.3977)	(0.0657, 0.3854)	(0.0223, 0.3659)
95% confidence interval	(0.1381, 0.4272)	(0.0270, 0.4079)	(0.0294, 0.4000)	(-0.0328, 0.4031)
90% confidence interval for difference from homogeneous preferences	-	(-0.1699, 0.0182)	(-0.1469, 0.0115)	**(-0.1814, -0.0035)**
95% confidence interval for difference from homogeneous preferences	-	(-0.1890, 0.0366)	(-0.1937, 0.0433)	**(-0.2435, 0.0069)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	**0.161**	**0.129**	**0.105**	**0.092**

Table 17: Regressions of log(household nondurable consumption) on log(household income) using the RCRE sample from 2003 to 2013

Estimated risk sharing coefficient $\widehat{\theta}$	log(household nondurable consumption)			
	(1)	(2)	(3)	(4)
log(income)	**0.3230****	**0.2408****	**0.2369****	**0.1915****
90% confidence interval	(0.2160, 0.4075)	(0.1016, 0.3746)	(0.0939, 0.3644)	(0.0494, 0.3363)
95% confidence interval	(0.2103, 0.4223)	(0.0694, 0.3796)	(0.0611, 0.3704)	(0.0162, 0.3457)
90% confidence interval for difference from homogeneous preferences	-	**(-0.1550, -0.0085)**	**(-0.1436, -0.0058)**	**(-0.2185, -0.0661)**
95% confidence interval for difference from homogeneous preferences	-	**(-0.1746, -0.0035)**	**(-0.1614, -0.0030)**	**(-0.2228, -0.0595)**
Heterogeneity:				
risk aversion	no	yes	no	yes
time preference	no	no	yes	yes
Estimated risk sharing coefficient $\widehat{\theta}$ for U.S. from Schulhofer-Wohl (2011)	**0.161**	**0.129**	**0.105**	**0.092**

Table 18: A summary of studies on testing risk sharing in China

Studies	Data	Preferences assumption	Estimation method	Point estimates of risk sharing coefficient
Xu (2008)	Aggregated provincial level household consumption and disposable income 1980-2004	Preferences homogeneity	OLS	$0.09 \sim 0.29$
Curtis and Mark (2010)	Provincial level consumption and output data 1954-2004	Preferences homogeneity	OLS	$0.50 \sim 0.67$
Du et al. (2011)	Provincial level consumption and output data 1990-2007	Preferences homogeneity	Fixed effects	$0.674 \sim 0.709$
Chan et al. (2014)	Provincial level consumption and output data 1952-2008	Preferences homogeneity	Fixed effects and random effects	$-0.020 \sim 0.7107$
Ho et al. (2015)	prefectural-level city retail sales and output data 1990-2010	Preferences homogeneity	OLS	$0.36 \sim 0.41$
Santaeulàlia-Llopis and Zheng (2016)	CHNS households level consumption and income data 1989-2009	Preferences homogeneity	OLS	$0.041 \sim 0.108$

Appendix A. Data compilation

Our empirical investigation on risk sharing at the household level in China is based on data from three household surveys, namely China Health and Nutrition Survey (CHNS), China Family Panel Survey (CFPS) and the RCRE (Research Center on the Rural Economy) Fixed Point Rural Household Survey. Depending on data availability and time span, we use the first and third survey to test consumption risk sharing at household level in China under different specifications of preferences heterogeneity, and we use the first and second survey to test whether preferences heterogeneity correlates with household income variability.

Appendix A.1. Data from CHNS

CHNS collects household level data across 1989 to 2011 in nine waves, 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, 2011. We select waves starting from 1997, because waves before 1997 do not provide sufficient information for us to compute household consumption. In each wave, CHNS selects around 200 primary sample units (PSU) in nine provinces in China, they are Guangxi, Guizhou, Henan, Hubei, Hunan, Jiangsu, Shandong, Heilongjiang and Liaoning[35]. Among those selected PSUs, around one third are from urban areas and the remaining two thirds from rural areas. Although CHNS is not designed as a representative household-level survey data in China, it is nonetheless one of longest available household-level survey datasets in China.

Table A1 provides summary statistics of data on consumption, income, transfer payment, and leisure we constructed from the CHNS. We briefly discuss how we construct them based on CHNS survey data[36].

Appendix A.1.1. Household income and leisure

We compute household income (net of transfer) as follows:

$$hhinc_{i,t} = wage_{i,t} + agr_{i,t} + buss_{i,t} + captl_{i,t} \tag{A1}$$

[35] In 1997, Liaoning was replaced by Heilongjiang. After 1997, Liaoning rejoined the survey. In 2011, Beijing, Shanghai and Chongqing joined the survey.

[36] We take reference from Santaeulàlia-Llopis and Zheng (2016) when we compute this data, while we differ from their methods in a few aspects. We refer readers to Santaeulàlia-Llopis and Zheng (2016) for detailed discussion of CHNS survey data.

where $hhinc_{i,t}$ is the income of household i in wave t net of transfer. $wage_{i,t}$ is the sum of household members wage income. $agri_{i,t}$ is household agriculture income. $buss_{i,t}$ is household income from business, and finally $captl_{i,t}$ is household capital income. Below we elaborate on each of these items in detail.

1. **Household labour earnings and leisure**. CHNS records household income from four main sources, labour earnings, agricultural income, business income, and capital income. Labour earnings for working individuals across waves 1997 to 2011 are extracted from the file *wages_00*. Labour earnings for an individual are defined as the sum of wage/salary $c8$ and all bonus $i19$ of primary and secondary occupations. As $c8$ is monthly wage/salary, while $i19$ is annual, we calculate annual labour earnings using $c8 * c3 + i19$, where $c3$ is the number of months an individual has worked on this occupation. Household labour earnings are the sum of the labour earnings of all working members.

Wages_00 also provide data on the following questions: 1). For how many days in a week, on average, did you work? ($c5$) 2). For how many hours in a day, on average, did you work? ($c6$). We compute hours reported working by each individual using $c5 * c6 * 52$. Then we use 8760 minus hours reported working by household head to measure leisure.

One problem with individual-level labour earnings is that, wage/salary, and agricultural labour income from collective entities at the individual level are collected from the adult survey of CHNS. In the survey, for those who work at collective agricultural entities (farming, fishing and livestock/poultry raising) as their primary or secondary occupation, apart from being asked about the salaries they earn from these occupations, they are asked again in detail about their agricultural income from these agricultural activities[37]. To not double count the labour earnings for those who work at collective agricultural entities, we either take their wage/salary from their primary or secondary occupation as their labour earnings, or we take their agricultural income from the agricultural activities as their labour earnings. Summing up labour earnings of individual members in each household, this gives us two measures of labor earnings at household level. The way we

[37] In the adult questionnaire, wage/salary data is collected from all adults who work. Agricultural income data is collected from all adults. For adults who reported themselves working at collective entities in the agricultural sector, their labour earnings could have been collected twice. However, for those adults who did not report themselves as working, their labour earnings from agricultural activities at collective entities may be collected just once.

compute individual level agricultural income is discussed in parallel with household agricultural income below for convenience of exposition.

2. **Agricultural income**

Agricultural income is reported at household and individual level. At household level, agricultural income is collected from five activities, farming, gardening, livestock/poultry, and fishing. The corresponding data files are *farmh_00*, *gardh_00*, *livet_00*, and *fishh_00*, respectively. At individual level, agricultural income is collected from those who work at the collective farming, livestock/poultry, and fishing entities. The corresponding data files are *farmg_00*, *livei_00*, and *fishi_00*.

The household income from farming is computed as total income from crops last year ($e14a$), plus values of crops consumed last year ($e16a$), minus yuan spent raising crops last year ($e12$) from *farmh_00*. We add $e16a$ because this is also part of the total output of farming.

The household gardening income is computed as yuan recorded for garden produce sold last year ($d5$) minus yuan spent on garden last year $d7$ from the file *gardh_00*.

Household income from livestock/poultry is computed as $f17 + f19 + f21 - f14$ across the livestock/poultry raised and the products such as eggs, milk, meat, wool, and fertilizer, where $f17$ is yuan recorded for livestock sold last year, $f19$ is value of livestock consumed last year, $f21$ is value of livestock given away last year, and $f14$ is yuan spent raising livestock last year. Data comes from the file *livet_00*.

Household fishing income is computed as $g11 + g13 + g15 - g16$, where $g11$ is income from fish business last year, $g13$ is value of fish consumed last year, $g15$ is value of fish given away last year, and $g16$ is total fish business expenses last year. Data is collected from the file *fishh_00*.

Individual farming income is collected from *farmg_00*. It is the sum of $e7$ and $e9$. The former is yuan recorded from collective farm last year, the latter is value of collective farm produce recorded last year. Individual fishing income is computed as $g7 + g9$ from file *fishi_00*, where $g7$ is yuan recorded for collective fishing, and $g9$ is value of fish recorded from collective farm last year. Individual livestock/poultry income is computed as $f7 + f9$ from file *livei_00*, where $f7$ is yuan recorded for collective livestock work last year, and $f9$ is value of livestock recorded from the collective.

Family agricultural income is taken as the sum of household farming, gardening, livestock/poultry and fishing. For individual agricultural income, it is used to calculate individual labour earnings[38].

3. **Business income**

Household business income data is summed up from individual business income data. It is from the file *busi_00*. Individuals are asked if they operate a small handicraft or small commercial business. We compute this income from $h3a - h4a$, where $h3a$ is weekly average business revenues, and $h4a$ is average weekly business expenses. Multiplying the differences by 52 generates annual business income at individual level. Summing this income across members of a household, we obtain household level business income.

4. **Capital income**

Household capital income data is provided from the file *oinc_00*. It includes income from leased land ($j2$), yuan recorded from asset rentals ($j3$) and yuan recorded from boarders last year ($j4$).

Appendix A.1.2. Household transfers

We compute household transfers as follows:

$$transf_{i,t} = sub_{i,t}^{wu} + sub_{it}^{gov} + pension_{i,t} + transf_{it}^{pri} \tag{A2}$$

where $transfer_{i,t}$ is the sum of all types of transfers received by household i at time t, $sub_{i,t}^{wu}$ and $sub_{i,t}^{wu}$ are the subsidies received by household members from work units and from governments summed across members, respectively. $pension_{i,t}$ is pension received by household members summed across members. $transf_{it}^{pri}$ is private transfers received by household members from relatives and friends. One of the differences from our measure of household transfer income and Santaeulàlia-Llopis and Zheng (2016)'s measure is that we do not include food coupons. This is because our sample starts from wave 1997, and food coupons became obsolete after 1993. The other difference is that we include other incomes (items $i101$ and $i103$) collected in wage data in subsidies from work units. Apart from these two differences, we follow Santaeulàlia-Llopis and Zheng (2016) to compile other components of household transfer income.

[38] This differs our household income measure from Santaeulàlia-Llopis and Zheng (2016). They take household agricultural income as household level agricultural income plus the sum of agricultural income of individual members within each household.

Appendix A.1.3. Household consumption

We employ two measures of household consumption for risk sharing tests, one is household food consumption, the other is household nondurable consumption.

1. **Household food consumption**. CHNS provides in its nutrition survey a three day record of household food consumptions related to meals by food items. The data on the quantity consumed of each food item are collected at household level and summarised in the file *nutri1_00*. Prices of food items at community level is provided in the community survey file *M12COMFP*. Prices of food items and quantities consumed are then matched by using food code provided in various versions of China Food Composition[39]. We multiply food quantities consumed with food prices to come up with food expenditure at household level.

CHNS provides different prices of food items. For a typical food item, it may provide prices from three different stores, namely large store, state-owned store, and free market. For a few vegetables and fruits at different stores, it may provide two different prices, which are highest price and lowest price. We use free market price to compute household food expenditure. To preserve the largest possible set of food items and their prices, for a subset of vegetables and fruits that potentially have two prices, we use either the highest or the lowest free market price as the price of that food item. This is due to the fact that 1). A significant portion of food items only have one price; 2). For a subset of food items that may have two prices, sometimes either the highest or the lowest price may be missing. We could use average free market price, which may force us to either drop these food items due to missing prices or to make further assumptions to fill in average prices. As such we opt for the straightforward way to just use either the highest or the lowest price for a few food items. As such, we compute two measures of food expenditures related to meals based on these two prices measures respectively[40].

Apart from food expenditure from meals, we also collect household beverage consumption from the CHNS adult survey, the relevant data are from the file *pexam_00*.

Then we compute households annual food consumption as the sum of three-day food consump-

[39]We use three versions of China Food Compositions to match food codes with corresponding food items in CHNS, which are Yang (1999); Yang et al. (2002); Yang (2004, 2009).

[40]This differs our food consumption measure from that of Santaeulàlia-Llopis and Zheng (2016) as their price measure is the average of the highest and lowest prices.

tion related to meals multiplied by 365 and divided by 3, plus the annual households beverage expenditure to come up with household food consumption $fc_{i,t}$ for household i in wave t:

$$fc_{i,t} = fcmeal_{i,t} + beverage_{i,t} \tag{A3}$$

where $fcmeal_{i,t}$ is household food consumption related to meals, $beverage_{i,t}$ is household beverage consumption.

2. **Household other nondurable consumption**. Household other nondurable consumption collected by CHNS includes medical expenditure, housing, and child care services[41]. We collect these expenditures and add them to household food consumption to come up with household nondurable consumption as follows:

$$c_{i,t} = fc_{i,t} + onc_{i,t} \tag{A4}$$

where $c_{i,t}$ is household nondurable consumption, $fc_{i,t}$ is household food consumption, $onc_{i,t}$ is household other nondurable consumption.

Appendix A.1.4. Risk and time preferences proxies

We collect three variables that are proxies for household head's degree of risk aversion. The first is whether a person smoked last year ($u25$), the second is whether a person drank beer or alcohol last year ($u40$), the third is whether a person participated in preventive health service during the last four weeks at the time of interview ($m47$). $u25$ and $u40$ are from the file *pexam_00*, $m47$ is from the file *hlth_00*.

We collect one variable that is proxy for household head's time preference, which is self-reported health condition (self-rated health)($u48a$). It ranges from 1 to 4, with 1 for excellent health and 4 for poor health.

In addition, we also collect household demographic variables from adult and household surveys of CHNS as control variables.

Appendix A.1.5. Data transformation and sample selection

After we obtain household level income and consumption data, we use price index provided by CHNS to inflate the nominal values to real values. We use *index_new* provided in the data file

[41]We follow Santaeulàlia-Llopis and Zheng (2016) in computing household other nondurable consumption. The difference is that we didn't include education expenditure, since it only appears in 2006 wave.

$c12hhinc$, which takes the price of urban Liaoning in 2011 as 1.

Then we use Krueger and Perri (2006)'s scale to come up with the adult equivalent household income and consumption.

We drop 1989, 1991 and 1993 waves since for these three waves, we do not have the complete food code table to compute consumption data. We select households with household head aged between 20 and 65. Then we trim the top and bottom 1% households in terms of their household incomes, and the top and bottom 1% in terms of their consumptions. Table A1 summarises the data we compiled from CHNS.

Appendix A.2. Data from CFPS

We use data from China Family Panel Studies (CFPS) to test the relevance of household time preferences on estimating risk sharing coefficient unbiasedly[42]. The CFPS was designed to document changes in Chinese society, economy, population, education, and health. It focuses on economic and social well-being of the Chinese people and aims to provide data that covers a wide range of areas such as economic activities, education attainment, family relationships, migration, and physical and mental health. The first wave was conducted in 2011, covering 14,960 households. The second wave includes 13,315 households. The CFPS data includes 25 provinces, municipalities, and autonomous regions except Hong Kong, Macau, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia and Hainan. It covers 95% of the Chinese total population and can be regarded as a nationally representative sample. The sampling strategy of CFPS is to first identify five "large provinces" (Shanghai, Liaoning, Henan, Gansu and Guangdong), from which half of the sample was generated by five independent sampling frames. The remaining half of the sample was from an independent sampling frame composed of the other 20 provinces ("small provinces"). It then implemented multistage Probability-Proportional-to-Size Sampling (PPS) with implicit stratification, with administrative units and socioeconomic status (SES) as main stratification variables. In 2010 wave, there were 640 primary sampling units (PSU), among which half were from the five "large provinces", while the other half were from the remaining 20 "small provinces". It is important to note that CFPS did not sample urban and rural areas separately, rather it sampled the Chinese population as a whole.

[42] Detailed information of CFPS could be found in CFPS user's manual 2010 available at http://www.isss.edu.cn/cfps/EN/Documentation/js/229.html.

In particular, we collect household income and total assets from family survey, and household head's self-rated health status from adult survey. We use the 2010 and 2012 waves, and select households with head aged between 20 and 65. We deflate the nominal variables using GDP deflator calculated from data of China Statistical Year Book. Then we trim the top and bottom 1% households in terms of their household incomes. Table A2 provides the summary statistics.

We also collect household demographic variables from adult and family survey of CFPS as control variables.

Appendix A.3. Data from RCRE Fixed Point Rural Household Survey

We use the RCRE (Research Center on the Rural Economy) Fixed Point Rural Household Survey to test whether institutional changes and labour market reforms implemented during the 1990s and early 2000s may have any effect on household risk sharing in China. The survey collected detailed household-level information on income, expenditure, labour supply and other household characteristics. When it started in 1986, it covered households in 272 villages in 28 provinces. Depending on village size, between 40 and 120 households were randomly surveyed in each village. In later surveys, surveyed villages increased to 360 in 31 provinces. On average, each survey covers more than 22,000 households. By agreement we are allowed to access a 10% sample of the RCRE data, which gives us a sample of around 2,000 households in each survey year. We then extract two subsamples from the whole sample from 1986 to 2013. One is from 1986 to 1991, when labour market reforms and the related institutional changes were not initiated. The other is from 2003 to 2013, when the aforementioned reforms had already been implemented.

Household income is calculated as net income (gross revenue less current expenditures, taxes and remittance to village community) from agriculture, animal husbandry and livestock, family businesses, plus wage income earned inside and outside the village, minus transfers[43]. Household consumption is measured by food consumption and also nondurable consumption, respectively. For both income and consumption, we deflate them using GDP deflator calculated using data from China Statistical Yearbook. We then trim the top and bottom 1% data of the distribution for each

[43]Benjamin et al. (2011) mentioned that after 2002, there were significant changes in survey design from 2003 that introduced serious comparability problems for income. This does not pose any serious problems for us, since we do not pool data from after 2002 together with that from before 2002. It is understandable that measures of income change in the survey significantly, as income sources for rural households have changed through the years.

Table A1: Summary statistics of CHNS consumption and income sample

Variable name	different measures	mean	sd
food consumption	1	7403.410	7570.376
	2	7411.763	7558.369
adult equivalent food consumption	1	2934.172	3008.879
	2	2936.504	3006.194
log (adult equivalent food consumption)	1	7.624	0.964
	2	7.633	0.942
annual nondurable consumption	1	7917.184	7914.671
	2	7925.626	7906.858
adult equivalent nondurable consumption	1	3145.109	3159.888
	2	3147.865	3159.706
log (adult equivalent nondurable consumption)	1	7.712	0.914
	2	7.718	0.899
annual income	1	13550.770	18021.230
	2	13557.530	18022.960
adult equivalent annual income	1	5561.711	7741.371
	2	5564.432	7742.328
log(adult equivalent annual income	1	8.262	1.240
	2	8.263	1.239
annual income plus transfer	1	16138.100	19676.500
	2	16144.870	19677.310
adult equivalent income plus transfer	1	6610.167	8389.105
	2	6612.896	8389.686
log(adult equivalent income plus transfer)	1	8.248	1.324
	2	8.250	1.324
annual income plus public transfer only	1	14391.920	18425.330
	2	14398.680	18426.760
adult equivalent income plus public transfer only	1	5913.464	7924.220
	2	5916.184	7925.049
log(adult equivalent income plus public transfer only)	1	8.180	1.343721
	2	8.181	1.344
annual income plus private transfer only	1	14988.290	18538.520
	2	14995.060	18539.750
adult equivalent income plus private transfer only	1	6132.051	7949.867
	2	6134.772	7950.633
log(adult equivalent income plus private transfer only)	1	8.229	1.303
	2	8.230	1.303
annual hours not working of household head	1	6461.322	1098.947
log(annual hours not working of household head)	1	8.755	0.215
Observations		16,813	
Households		3,550	
Years of data per household	:		
mean		4.607	
minimum		1	
25th percentile		4	
75th percentile		6	
maximum		6	

income and consumption measures.

Labour supply data during 1986 to 1991 surveys were provided not at individual member level, but at household level. In addition, labour supply was not recorded as hours worked, but as "days laboured"[44], which equals eight hours worked on average. After 2003, RCRE survey started to provide hours worked data at individual level within each household. Table A3 and A4 below shows the summary statistics of our RCRE sample.

Appendix B. Details of GMM tests

Schulhofer-Wohl (2011) provides details of econometric methods of factor and GMM estimations. Because household consumption and income data from CHNS come from unevenly spaced waves, in this section we elaborate a bit on how we perform GMM tests on our data[45].

Since the GMM tests allow nonseparability between consumption and leisure, the estimation equation becomes:

$$y_{it} = \frac{\log \lambda_i}{\gamma_i} + \frac{1}{\gamma_i} d_t + t\frac{\log \beta_i}{\gamma_i} + \theta x_{it} + \mu z_{it} + \varepsilon_{it} \tag{B1}$$

where y_{it} is the log household consumption, x_{it} is log household income, and z_{it} is log hours of leisure of the head.

GMM tests are based on the following moment condition:

$$E\left[v_{is} e_{it}\right] = 0 \tag{B2}$$

Table A2: Summary statistics of CFPS sample

Variable name	mean	sd
annual income	43356.69	60896.34
total asset	270029.7	688904.1
smoking	0.4676	0.4990
drinking	0.2793	0.4487
self-rated health	2.9681	1.5006
Observations	13,308	

[44] In Chinese pinyin it is Tou Gong Ri.

[45] Factor model estimation, as it is based on quasi-fixed effects transformation, Schulhofer-Wohl (2011)'s factor model test could be directly applied on CHNS data.

Table A3: Summary statistics of RCRE sample from 1986 to 1991

Variable name	mean	sd
annual household food consumption	1143.292	651.430
log(annual household food consumption)	6.891	0.566
annual household nondurable consumption	1566.166	884.429
log(annual household nondurable consumption)	7.207	0.564
annual household income	2498.571	1955.930
log(annual household income)	7.548	0.800
annual "days laboured"[a] of working household members	131.000	223.698
log(annual "days laboured" ...)	4.998	1.236
Observations		12,258
Households		2,475
Years of data per household	:	
mean		4.625
minimum		0
25th percentile		4
75th percentile		6
maximum		6

[a] From 1986 to 1991, the RCRE surveys report labour supply at household level in units of "days laboured" (Tou Gong Ri). For each "day laboured", it is equivalent to eight hours worked.

Table A4: Summary statistics of RCRE sample from 2003 to 2013

Variable name	mean	sd
annual household food consumption	1608.698	1139.219
log(annual household food consumption)	7.148	0.715
annual household nondurable consumption	2038.800	1336.461
log(annual household nondurable consumption)	7.420	0.653
annual household income	6504.291	5558.137
log(annual household income)	8.452	0.893
annual hours not working of household head	5929.868	1195.351
log(annual hours not working of household head)	8.865	0.137
Observations		18,464
Households		2,149
Years of data per household	:	
mean		8.314
minimum		0
25th percentile		7
75th percentile		11
maximum		11

where v_{is} represents the instrumental variable, e_{it} is the error term in eq. (B1). This moment condition is assumed to hold for all s and t. In order to avoid weak instruments, we use v_{it} and its nearest lag $v_{i,t-q}$ as instruments.

1. **No heterogeneity**

When risk and time preferences are assumed to be homogeneous across households, we can normalize $\gamma_i = 1$ and $\log \beta_i = 0$ for all i. Since the six waves of CHNS are 1997, 2000, 2004, 2006, 2009, and 2011, we take difference between adjacent waves:

$$\Delta_s y_{i,t} = \Delta_s d_t + \theta \Delta_s x_{i,t} + \mu \Delta_s z_{i,t} + \Delta_s \varepsilon_{i,t} \tag{B3}$$

where $\Delta_s \zeta_{i,t} = \zeta_{i,t} - \zeta_{i,t-s}$. For 2000, 2004, 2006, 2009 and 2001 waves, taking differences between adjacent waves requires s to be 3, 4, 2, 3, and 2, respectively.

We use $\mathbf{h_{it}} = [1 \quad \Delta_s z_{i,t} \quad \Delta_p z_{i,t-s}]$ as instrumental variables. Here $\Delta_s z_{i,t}$ is the pseudo "first difference" of $z_{i,t}$, which means it is obtained by taking difference between adjacent waves, and s depends on lag years between adjacent waves. $\Delta_p z_{i,t-s}$ is the pseudo "first lag" of $\Delta_s z_{i,t}$, as the lag p also depends on lag years between adjacent waves. For example, for wave 2011, we have the following equation:

$$\Delta_2 y_{i,2011} = \Delta_2 d_{2011} + \theta \Delta_2 x_{i,2011} + \mu \Delta_2 z_{i,2011} + \Delta_2 \varepsilon_{i,2011} \tag{B4}$$

The instrumental variables here are $\mathbf{h_{i,2011}} = [1 \quad \Delta_2 z_{i,2011} \quad \Delta_3 z_{i,2009}]$, where $\Delta_2 z_{i,2011} = z_{i,2011} - z_{i,2009}$, and $\Delta_3 z_{i,2009} = z_{i,2009} - z_{i,2006}$. For all subsequent cases, this is also the instruments vector we use. One reason for this is to preserve as much data as we could, as long as condition in eq. B2 is satisfied.

If leisure and its lags are uncorrelated with ε_{it} and its lags, the following moment conditions hold for waves from 2000 to 2011:

$$E\left[\mathbf{h_{it}}\left(\Delta_s y_{i,t} - \Delta_s d_t - \theta \Delta_s x_{i,t} - \mu \Delta_s z_{i,t}\right)\right] = \mathbf{0} \tag{B5}$$

To test complete risk sharing when assuming homogeneous preferences across households, we could use eq. B5 to test whether θ is different from zero.

2. **Heterogeneity only in time preferences**

If time preferences are allowed to differ among households, the right-hand side of eq. B1 now includes a household specific time trend. We could take second differences among waves[46]:

$$\Delta^2_{psq} y_{it} = \Delta^2_{psq} d_t + \theta \Delta^2_{psq} x_{i,t} + \mu \Delta^2_{psq} z_{i,t} + \Delta^2_{psq} \varepsilon_{i,t} \tag{B6}$$

where $\Delta^2_{psq}\zeta_{i,t} = (\zeta_{i,t} - \zeta_{i,t-p}) - (\zeta_{i,t-s} - \zeta_{i,t-q})$. Due to unevenly spaced waves in CHNS, in order to eliminate the household specific time trend, it is required that $t-(t-p) = (t-s)-(t-q)$, which is $p = q - s$. This gives us two data points of y_{it} for household i, which are as follows:

$$\Delta^2_{2,5,7} y_{i,2011} = (y_{i,2011} - y_{i,2009}) - (y_{i,2006} - y_{i,2004}) \tag{B7}$$

$$\Delta^2_{3,9,12} y_{i,2009} = (y_{i,2009} - y_{i,2006}) - (y_{i,2000} - y_{i,1997}) \tag{B8}$$

If leisure and its lags are uncorrelated with the error term, the following moment conditions hold for the above two waves of differenced data:

$$E\left[\mathbf{h_{it}}\left(\Delta^2_{psq} y_{it} - \Delta^2_{psq} d_t - \theta \Delta^2_{psq} x_{i,t} - \mu \Delta^2_{psq} z_{i,t}\right)\right] = \mathbf{0} \tag{B9}$$

Test of complete risk sharing could be performed by estimating θ using the above moment conditions, and evaluate if it is significantly different from zero.

3. **Heterogeneity only in risk preferences**

If households differ only in their risk preferences, we could take difference between adjacent waves using eq. B1:

$$\Delta_s y_{i,t} = \frac{1}{\eta_i}\Delta_s d_t + \theta \Delta_s x_{i,t} + \mu \Delta_s z_{i,t} + \Delta_s \varepsilon_{i,t} \tag{B10}$$

We could perform a quasi-differencing (Ahn el al., 2001) on eq. B10 to get:

$$\begin{aligned}\Delta_s y_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}}\Delta_q y_{i,t-s} = \theta &\left(\Delta_s x_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}}\Delta_q x_{i,t-s}\right) \\ &+ \mu\left(\Delta_s z_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}}\Delta_q z_{i,t-s}\right) + \Delta_s \varepsilon_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}}\Delta_q \varepsilon_{i,t-s}\end{aligned} \tag{B11}$$

where s and q depend on time lag between two adjacent waves. For example, for wave 2011, if

[46]Here we relax the restriction of adjacent waves, because for our data, allowing nonadjacent waves would help provide more data for estimation.

we take a quasi-differecing, we obtain:

$$\Delta_2 y_{i,2011} - \frac{\Delta_2 d_{2011}}{\Delta_3 d_{2009}} \Delta_3 y_{i,2009} = \theta \left(\Delta_2 x_{i,2011} - \frac{\Delta_2 d_{2011}}{\Delta_3 d_{2009}} \Delta_3 x_{i,2009} \right) + \mu \left(\Delta_2 z_{i,2011} - \frac{\Delta_2 d_{2011}}{\Delta_3 d_{2009}} \Delta_3 z_{i,2009} \right) + \Delta_2 \varepsilon_{i,2011} - \frac{\Delta_2 d_{2011}}{\Delta_3 d_{2009}} \Delta_3 \varepsilon_{i,2009} \tag{B12}$$

where $s = 2$ indicates the two-year gap between 2011 and 2009, $q = 3$ indicates the three-year gap between 2009 and 2006.

We observe that in eq. B11, there is no household specific risk preference parameter η_i. The following moment conditions hold for waves from 2004 to 2011:

$$E\left[\mathbf{h_{it}}\left[\Delta_s y_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}} \Delta_q y_{i,t-s} - \theta \left(\Delta_s x_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}} \Delta_q x_{i,t-s} \right) - \mu \left(\Delta_s z_{i,t} - \frac{\Delta_s d_t}{\Delta_q d_{t-s}} \Delta_q z_{i,t-s} \right)\right]\right] = \mathbf{0} \tag{B13}$$

We could use eq. B13 to test full insurance by estimating θ and test if it is significantly different from zero, under the assumption of homogeneous time preferences but heterogeneous risk preferences among households.

4. **Heterogeneity in both risk and time preferences**

We could take quasi-difference of eq. B7 and B8 to eliminate household specific risk preferences η_i. This is because due to data limitation, for this case we only have one observation for each household that appears consecutively in all waves. The moment conditions that are valid when both risk and time preferences are heterogeneous are:

$$E\left[\mathbf{h_{i,2011}}\left[\Delta^2_{2,5,7} y_{i,2011} - \frac{\Delta^2_{2,5,7}}{\Delta^2_{3,9,12}} \Delta^2_{3,9,12} y_{i,2009} - \theta \quad \Delta^2_{2,5,7} x_{i,2011} - \frac{\Delta^2_{2,5,7}}{\Delta^2_{3,9,12}} \Delta^2_{3,9,12} x_{i,2009} \right) - \mu \quad \Delta^2_{2,5,7} z_{i,2011} - \frac{\Delta^2_{2,5,7}}{\Delta^2_{3,9,12}} \Delta^2_{3,9,12} z_{i,2009} \right)\right]\right] = 0 \tag{B14}$$

As such, when we include leisure on the right-hand side of eq. B14, the estimation model is exactly identified, so we are unable to perform the overidentification test for this case.

Risk sharing test when both risk and time preferences are heterogeneous could be performed by using eq. B14 to estimate θ and see if it is significantly different from zero.

Identification in the above four sets of moment conditions requires that the instruments be correlated with the right-hand-side variables. As noted in Schulhofer-Wohl (2011), Ahn et al. (2001) show that identification in eq. B11 and B14 also requires that an instrument be correlated with η_i. This implies that risk preferences must be heterogeneous.