Heterogeneous preferences and risk sharing at households level in China

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Abstract

This paper investigates the degree of risk sharing across households in China with heterogeneous risk and time preferences. Standard tests assume homogeneous preferences across households, which may bias the true risk sharing degree to different directions, if risk and time preferences are correlated with variations of household income. We use household data from 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. These two correlations bias the true degree of risk sharing toward opposite directions if homogeneous preference is assumed. We apply the factor and GMM estimation techniques from Schulhofer-Wohl (2011) to the data. We find that around 30% of household income shocks would pass through to household consumption when households are assumed to have homogeneous preferences. When both risk and time preferences are allowed to differ across households, this number reduces to around 3% and become insignificant, indicating a much higher degree of risk sharing. By comparing this result with that of U.S., we find that the degree of risk sharing across households in China is similar to that in U.S.. In addition, we find that when transfer incomes are included into household income, the estimated risk sharing coefficients remain roughly unchanged. We provide suggestive evidence that the institutional reforms in the sample period that give Chinese households more freedom in their labor market choices do contribute to better household risk sharing.

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1. Introduction

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

Previous work has been done 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, which provides a full set of Arrow-Debreu securities to facilitate risk sharing among agents with heterogeneous income risks, 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 still 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, 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 that on one hand, 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, public social insurance system and financial markets (Blundell et al., 2008). A number of studies specifically focus on investigating the effects of one of the potential consequence of self-insurance–precautionary saving 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 utilize to insure themselves against shocks (Townsend, 1994). For example, households could obtain financial help from friends and relatives when hit by negative income shocks. In addition, adjustment of durable goods is commonly used by households in developing rural areas for insurance. Social insurance system, which has been undergoing continuous reforms in China since mid-1990s[1], also provides risk sharing opportunities for households. Recent studies, such as Chiappori et al.

[1]See Dong (2009), Meng (2012), Rickne (2013).

(2014), show that degree of risk sharing is higher in rural Thailand than in U.S.. As such, whether an economy has more advanced markets does not seem to imply a higher degree of risk sharing pe ser.

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[2]. This point is of particular importance for China for two reasons. First, household income risk increased substantially since late 1990s [3]. Empirical studies show that households income risk remained relatively stable till the second half of 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 enabled individuals with more freedom in their labor market choices[4]. It became less difficult for labor market participants to sort themselves into different occupations according to their own preferences from late 1990s onwards compared to before. As such, neglecting risk preferences heterogeneity when it is in fact present may lead to incorrect conclusion on whether China has full insurance, particularly when data after later 1990s is being utilized.

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[5]. 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 is not readily available in China for the past decade. However, aggregated data may not be appropriate in reflecting what's going on at micro level before aggregation (Deaton, 1992). Since the ul-

[2]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.

[3]From 1989 to 2009, wage inequality measured by Gini coefficient has increased from 0.26 to 0.38, while at the same period, 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 labor income, leads to opportunities to raise aggregate productivity by concentrating works among more productive workers (Heathcote et al., 2008).

[4]Detailed discussion is provided in Section 2.

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

timate goal of risk sharing test 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 at testing the degree of risk sharing at household level in China, taking into account the effects of heterogeneous preferences. By employing a relatively long household survey data that spans from 1997 to 2011 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 standard risk sharing test induced by assuming homogeneous preferences in the presence of heterogeneous preferences to produce an unbiased risk sharing coefficient. As such, we are able to address the above three problems simultaneously. By utilizing the econometric techniques developed by Schulhofer-Wohl (2011), which is suitable for panels with large cross-sectional units but small 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. Our main findings are as follows. *First*, risk sharing at household level in China is complete. In other words, households in China do enjoy full insurance against income risks. In addition, compared to tests based on Panel Survey of Income Dynamics (PSID) data of U.S. households (Schulhofer-Wohl, 2011), the degree of risk sharing at household level in China is similar to that across households in U.S.. However, this similarity breaks up if one neglects risk and time preferences heterogeneity. Estimating the standard risk sharing equation assuming homogeneous preferences for households in China leads to an upward biased coefficient which indicates that households do not enjoy full insurance in China and enjoys less consumption insurance compared to U.S. households. *Second*, for more risk tolerant households, their incomes correlate more positively with the aggregate shock, which tends to bias the standard risk sharing coefficient upward. For households with less patience, their incomes correlate more positively with the aggregate shock, which tend to bias the standard risk sharing coefficient downward. This latter effect is in sharp contrast to that of U.S. households in Schulhofer-Wohl (2011), where incomes of households with more patience correlate more positively with the aggregate shock. *Third*, the degree of risk sharing at household level in China does not seem to improve significantly when either public transfer or private transfer payments, or both are included into household income. This shows that households do not seem to benefit much from public social insurance system or private social networks in terms of improving their insurance ability against risks.

This paper is among one of the first attempts in the literature to test risk sharing at 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 from several aspects. *First*, preferences heterogeneity have been shown to have important effects on people's choices of occupation (Fuchs-Schündeln and Schündeln, 2005; Bonin et al., 2007; Schulhofer-Wohl, 2011). As such, an unbiased estimate of the true risk sharing degree at household level is of great importance for public policy designed to improve household welfare. Policies that try to improve household welfare by eliminating aggregate risk could result in some sufficiently risk-tolerant households suffering welfare loss (Schulhofer-Wohl, 2008), although it unambiguously improves households welfare when preferences are homogeneous. Thus, whether preferences heterogeneity play an important role in households' decision of labor supply is crucial for policy design. *Second*, higher wage dispersion that arises when the economy undergoes profound structural change presents opportunities to raise aggregate productivity. Heathcote et al. (2008) has shown that welfare gains from perfectly insuring income risk is much larger than welfare gains from eliminating income risk. This suggests that Chinese government could increase income insurability through developing its insurance markets, which could have more welfare improving effect compared to progressive taxes which tend to eliminate income risk. However, in order to do so, one needs to obtain an unbiased estimate of risk sharing in the first place. *Last but not least*, since we find that Chinese households contrast with their U.S. counterparts in that more patient households bear less aggregate risk, this empirical finding in itself calls for more research in this direction due to its welfare implication from both consumption insurance and long term growth (Dohmen et al., 2015).

The rest of the paper is organized as follows. Section 2 presents a brief description of institutional background in China during the period that we focus on. Section 3 presents the model and data description. Section 4 presents empirical evidence showing whether heterogeneity in preferences has any effect on the correlation of household income with aggregate output at household level in China. Section 5 presents 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 mid 1990s to late 2000s over which the data span. We focus on reforms that have the potential to impact households risk sharing abilities.

2.1. Before mid 1990s

China started its market oriented economic reform in late 1970s in rural area. Collective farming under the Commune system was abandoned and households responsibility system had been adopted (Chow, 2004). This has led to significant increase of rural productivity, as households enjoyed residual claims to their own production efforts. At mid-1980s, rural unemployment became a serious problem, and rural residents were encouraged to set up Towns and Village Enterprises (TVEs), which helped absorb redundant labor from agricultural production (Huang, 2008). Meanwhile, the Chinese government started to set up Special Economic Zones (SEZ) in a few cities[6], which coupled with development of cities called for more labor input. Thus, limited rural-urban migrants emerged (Meng, 2012), although at the same time city governments stringently restricted rural migrants (Zhao, 2003).

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

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

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

2.2. During 1990s to late 2000s

After experimenting with economic reforms in the 1980s, China continued its reforms in the 1990s, with a particular focus on urban sectors. One of the major structural reform during mid 1990s was a policy called "Holding on to the Large, Letting Go of the Small", which aims at privatizing small and medium-sized State Owned Enterprises (SOEs) while retaining control of large enterprises. After its implementation in 1995, industrial output share of state and collective sectors shrank from over 90 percent in 1990 to 70 percent in 1997, and further reduced to 30 percent in 2008[7]. This was accompanied by massive layoff of the state sector in urban areas, and by a continuingly thriving urban private sector. During 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 percent in 1994 to over 50 percent 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

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

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

cities increased from 39 million in 1997 to 145 million by 2009 (Iyer et al., 2013). In addition, starting from early 1990s, college graduates in China were gradually not guaranteed with job positions after graduation by central planning from the Ministry of Education, and this job assignment system was fully abandoned after 2000[8]. Meanwhile, in 1997, wholly private enterprises owned by entrepreneurs received the official accreditation.

These reforms have profound impact on both urban and rural households in China. As urban labor market became more open to job seekers and employers of various kinds, and entrepreneurship were encouraged, Chinese citizens had more freedom on their occupation choices from mid 1990s onwards. Rather than being strictly bounded by *Hukou* and other institutional restrictions, and having few options in job choices, it now became possible for people to select jobs according to their preferences. As such, for less risk averse individuals, it became much easier for them to choose jobs that allow them to bear more aggregate risk of the economy. This in turn could facilitate risk sharing across households in China. As such, empirical test of risk sharing needs 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 4 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). Basic Pension Scheme was also implemented in 1997 for urban employees. All these were to replace the Labor Insurance Scheme (LIS) set up in 1951 for urban employees, which provided non-wage benefits to urban workforce from cradle to death. The new social insurance systems of urban workers feature contributions from both employees and employers, while the previous system required no premium payment from employees. For urban unemployed, the Basic Social Medical Insurance Scheme for Urban Residents (BSMISUR) were carried out for pilot trial and a total of 88 cities joined until 2007. For rural residents, the New Rural Cooperative Medical Insurance Scheme (NRCMIS) was in pilot trial in 2003 and then implemented throughout the rural area of the country to provide health insurance to rural people. By 2007, 85.6 percent counties in China had implemented the scheme, and 86.2 percent rural population in these counties had been enrolled (Dong, 2009).

Although the social insurance systems implemented so far covers a farely large share of the whole population, the effectiveness of it is still questionable. This is probably due to two reasons. First, the Tax Reform implemented in 1994 dramatically increased the

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

share of the central government over tax revenues, which was more than doubled from 22 percent in 1993 to around 49 to 56 percent after 1994 (Lai et al., 2014). Meanwhile, revenue recentralization was not accompanied by expenditure recentralization, the central government's share in the total government expenditure fell from 30 percent in 1994 to 18 percent in 2010 (Lai et al., 2014). Since the social insurance reforms listed above involves contribution from both the central and local governments, insufficient revenues at subnational level could have impaired the implementation of these schemes[9]. As such, it is an empirical question whether social insurance do provide 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 places more risks to less risk averse households. When preferences are heterogeneous among households, standard tests of efficient risk sharing in the literature which assume homogeneous preference fail to capture the true Pareto-efficient allocation and tend to generate spurious rejections of efficient risk sharing[10].

Assume an endowment economy with N households. Households have time-separable expected utility functions over a single consumption good, c. The state of the economy at each date t is denoted by s_t.

The Pareto-optimal consumption allocations are derived from the planning problem. The social planner maximizes a weighted sum of households' utilities as follows:

$$\max \sum_{i=1}^{N} \lambda_i E_0 \sum_{t=0}^{T} \beta_i^t u\left(c_{it}(s_t)\right) \tag{1}$$

where λ_i is the Pareto weight assigned to household i. Assuming that households have CRRA preferences, eq. 1 becomes:

$$\max \sum_{i=1}^{N} \lambda_i E_0 \sum_{t=0}^{T} \beta_i^t \frac{[c_{it}(s_t)]^{1-\eta_i}}{1-\eta_i} \tag{2}$$

where η_i denotes the relative risk aversion of household i that varies across households[11].

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

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

[11]Schulhofer-Wohl (2007, 2011) shows that heterogeneity in η_i can represent differences in utility func-

The feasibility constraint of this economy is that the total of households' consumption should be no larger than the aggregate endowment available in the economy at date t in state s_t[12].

$$\sum_{i=1}^{N} c_{it}(s_t) \leq e^A(s_t) \text{ for all } s_t \tag{3}$$

where $e^A(s_t)$ denotes aggregate endowment available in the economy at date t.

Take a derivative with respect to $c_{it}(s_t)$, the first-order conditions for the maximization problem in (2) subject to (3) are:

$$\beta_i^t \lambda_i \left[c_{it}^*(s_t)\right]^{-\eta_i} = \frac{\mu(s_t)}{\pi(s_t)} \tag{4}$$

where $\mu(s_t)$ is the Lagrange multiplier on the feasibility constraint (3), $\pi(s_t)$ is the probability that state s_t occurs. Define $\rho(s_t) = \frac{\mu(s_t)}{\beta^t \pi(s_t)}$, and temporarily assuming homogeneous time preference across households and suppressing state dependent s_t, eq. 4 becomes:

$$\lambda_i \left(c_{it}^*\right)^{-\eta_i} = \rho_t \tag{5}$$

ρ_t depends on aggregate consumption, which is constant across households i. As such, conditional on aggregate consumption and the Pareto weights, the determination of individual households' consumption allocations is independent of households' idiosyncratic variables, such as endowments, if consumption risk sharing is efficient.

Taking logs of eq.(5) and assuming that consumption is measured with multiplicative error as shown by $c_{it} = e^{\varepsilon_{it}} c_{it}^*$, we obtain:

$$\log c_{it} = \frac{\log \lambda_i}{\eta_i} + \frac{1}{\eta_i}\left(-\log \rho_t\right) + \varepsilon_{it} \tag{6}$$

Eq.(6) shows that for households that have larger coefficient of relative risk aversion η_i, aggregate shock ρ_t have a smaller effect on their consumption. One could test for efficient consumption risk sharing by adding households idiosyncratic variable X_{it} to eq. (6):

$$\log c_{it} = \frac{\log \lambda_i}{\eta_i} + \frac{1}{\eta_i}\left(-\log \rho_t\right) + \theta X_{it} + \varepsilon_{it} \tag{7}$$

tions or in relative risk aversions across households with identical non-CRRA preferences but different consumption levels.

[12]If storage is possible, then aggregate consumption of all households should not exceeds aggregate endowment minus aggregate storage.

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 households idiosyncratic variable is household income[13], $\log y_{it}$, where y_{it} denotes income of household i in period t.

One of the crucial assumptions made in previous analyses of risk sharing, as pointed out by Schulhofer-Wohl (2011) and Mazzocco and Saini (2012), is that households under investigation have identical risk preferences, $\eta_i = \eta$. Replacing η_i by η, and X_{it} by $\log y_{it}$, eq.(7) becomes:

$$\log c_{it} = \frac{\log \lambda_i}{\eta} + \frac{1}{\eta}(-\log \rho_t) + \theta \log y_{it} + \varepsilon_{it}^{equal} \tag{8}$$

The above equation is simpler in that the second term related to the aggregate shock now becomes a time dummy variable and has identical effect on household consumption allocation. However, if the true model is eq.(7) and one mistakenly estimates eq. (8), the error term in eq.(8) absorbs the heterogeneous effect of aggregate shock on households consumption:

$$\varepsilon_{it}^{equal} = \left(\frac{1}{\eta_i} - \frac{1}{\eta}\right)(-\log \rho_t) + \varepsilon_{it} \tag{9}$$

If $Cov\left(\log y_{it}, \varepsilon_{it}^{equal}\right) = 0$, the least square estimator of the coefficient on income in eq. (8) is unbiased. However, if $Cov\left(\log y_{it}, \varepsilon_{it}^{equal}\right) > 0$ (< 0),the estimator is biased upward (downward).

Assume that households income is determined by the following equation:

$$\log y_{it} = \phi_i \omega_t + \xi_{it} \tag{10}$$

where ω_t is a common shock, ϕ_i is the semielasticity of household i's income to the common shock, ξ_{it} is an idiosyncratic shock to household i's income[14]. Assuming that the distributions of ϕ_i and η_i are stationary, and ξ_{it} and ε_{it} are i.i.d., we have:

[13]For example, Cochrane (1991); Mace (1991); Townsend (1994) use this variable to test full insurance at household level in U.S. and in rural Thailand.

[14]This assumption is key to illustrate 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).

$$
\begin{aligned}
Cov\left[\log y_{it}, \varepsilon_{it}^{equal}\right] &= -Cov\left[\phi_i \omega_t + \xi_{it}, \left(\frac{1}{\eta_i} - \frac{1}{\eta}\right)\log \rho_t + \varepsilon_{it}\right] \\
&= -Cov\left[\phi_i \omega_t, \left(\frac{1}{\eta_i} - \frac{1}{\eta}\right)\log \rho_t\right] \\
&= -Cov\left(\omega_t, \log \rho_t\right) Cov\left(\phi_i, \frac{1}{\eta_i}\right) \qquad (11)
\end{aligned}
$$

$Cov\left(\omega_t, \log \rho_t\right) < 0$, 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). $\frac{\partial \log \rho_t}{\partial \sum_i^N c_{it}} < 0$, 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 $Cov\left(\phi_i, \frac{1}{\eta_i}\right) > 0$. That is to say, the estimated θ in eq.(8) 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 that assumes the absence of this heterogeneity. We briefly show this below.

Temporarily shut down the heterogeneity in risk preference, but allow time preferences to be different among different households, the first order condition in eq.(4) changes to:

$$
\beta_i^t \lambda_i \left[c_{it}^*(s_t)\right]^{-\eta} = \psi(s_t) \qquad (12)
$$

where $\psi(s_t) = \frac{\mu(s_t)}{\pi(s_t)}$. Taking log at both side of eq.(12):

$$
\log c_{it} = \frac{1}{\eta}\log \lambda_i + \frac{1}{\eta} t \log \beta_i - \frac{1}{\eta}\log \psi_t + \varepsilon_{it} \qquad (13)
$$

Assuming homogeneous time preference when the true model has heterogeneous time preference, one estimates the following model for full insurance:

$$
\log c_{it} = \frac{1}{\eta}\log \lambda_i + \frac{1}{\eta} t \log \beta - \frac{1}{\eta}\log \psi_t + \log y_{it} + \varepsilon_{it}^{equalt} \qquad (14)
$$

where $\varepsilon_{it}^{equalt} = \frac{1}{\eta} t \left(\log \beta_i - \log \beta\right) + \varepsilon_{it}$.

Examine the covariance between aggregate shock and the above error term in eq.(14), we have:

$$
\begin{aligned}
Cov\left[\log y_{it}, \varepsilon_{it}^{equalt}\right] &= Cov\left[\phi_i\omega_t + \xi_{it}, \frac{1}{\eta}t\left(\log\beta_i - \log\beta\right) + \varepsilon_{it}\right] \\
&= Cov\left[\phi_i\omega_t, \frac{1}{\eta}t\left(\log\beta_i - \log\beta\right)\right] \\
&= Cov\left(\omega_t, \frac{t}{\eta}\right)Cov\left(\phi_i, \left(\log\beta_i - \log\beta\right)\right) \qquad (15)
\end{aligned}
$$

The range of t is limited in most available longitudinal survey data. This trend t of consumption is very likely to be positively correlated with aggregate consumption (Blundell et al., 2013), as well as aggregate shock, so we have $Cov\left(\omega_t, \frac{t}{\eta}\right) > 0$. As a result, neglect of heterogeneity of time preferences across households (in the absence of heterogeneity of risk preferences) also leads to biased estimator of full insurance: the estimator θ in eq.(14) is biased upward when $Cov\left(\phi_i, \log\beta_i\right) > 0$, and downward when $Cov\left(\phi_i, \log\beta_i\right) < 0$. When both heterogeneity in time and risk preferences are present, the bias will depend on the relative strength of both the covariance between aggregate shock and degree of risk averse, and between aggregate shock and time preference.

By using PSID and HRS (The Health and Retirement Study) data from the U.S., Schulhofer-Wohl (2011) finds that people with more risk tolerance do 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, his risk sharing results show that the estimated $\widehat{\theta}$ is biased upward when neglecting time preferences heterogeneity (controlling for risk aversion heterogeneity). This indicates that in the U.S., $Cov\left(\phi_i, \log\beta_i\right) > 0$, which shows that incomes tend to correlate more strongly with aggregate shock for people that are more patient, although he didn't test this empirically using household level data in U.S..

In the next section, we utilize 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 correlates more strongly for people with less risk aversion or not. In addition, we also test whether incomes correlates more strongly for people with less patience or not. This would help shed light on potential bias in the estimated risk sharing parameter $\widehat{\theta}$ when assuming the absence of preference heterogeneity.

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

4.1. Risk preferences and household income

In this subsection, we empirically test whether less risk averse people tend to choose occupations with income that correlates more strongly with aggregate shock in China.

In the literature, usually there are two ways to gauge whether a person is more risk averse or less so. The first is by eliciting people's risk preferences through asking them hypothetical questions related to their future income process[15]. This has been used by Health and Retirement Survey (U.S.), several European household surveys, the Survey of Consumer Finance (U.S.) and China Household Finance Survey (CHFS)[16].

The second way is to infer people's risk preferences by examining their behaviors. Barsky et al. (1997) find that people who are less risk averse have more risky behaviors like smoking, drinking and not having insurance. Similar correlation between risk aversion and risky behaviors 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 behaviors, such as smoking, drinking, wearing seat belts, and so on. For example, Cutler et al. (2008) proxy risk preferences by five measures of behaviors: smoking, drinking, job-based mortality risk, receipt of preventive health care, and use of seat belts.

The China Health and Nutrition Survey (CHNS), which contains information on health behaviors as well as income and other demographic information of households in China, provides us with information to test the hypothesis regarding whether risk preferences have any effect on the correlation between household income and the aggregate risk of the economy[17]. It asks the following questions on respondents' health behaviors: 1). Whether one smokes cigarettes or pipes? 2). Whether one drinks beer/alcohol/liquor? 3). Whether one has utilized preventive health service in the last 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). Labor earnings; 2).Agricultural income; 3). Business income; 4). Capital income[18]. We compute household income (excluding transfer income) by summing up labor earnings of household members, agricultural income, business income and capital income at household level. We then compute the real household income by deflating nominal income using Consumer Price Index provided by CHNS for each province. We further compute the adult-equivalent household income using the scale provided by Krueger and Perri (2006).

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

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

[17]For a more comprehensive description of the dataset, see Santaeulàlia-Llopis and Zheng (2016) and the website of the CHNS data `http://www.cpc.unc.edu/projects/china/`.

[18]Detailed information on data compilation could be found in Appendix A.

We restrict our analysis to households with head whose age is between 20 and 65. We drop those households that appear less than 3 times in the survey, and that did not answer the above-mentioned three behavior questions that reflect their risk tolerance. In addition, we trim the top and bottom 1% households in terms of their position in income and consumption distribution in each wave. This gives us 16,813 observations for 3,550 households[19].

We estimate the following specification:

$$\log(y_{it}) = \gamma_0 + \gamma_1 \cdot behavior_{it} + \gamma_2 \cdot aggshock_t + \gamma_3 \cdot behavior_{it} \times aggshock_t + \mathbf{x_{it}}\mathbf{\Phi} + \upsilon_{it} \quad (16)$$

where $aggshock_t$ represents aggregate shock, and is proxied by per capita GDP from China Statistical Yearbooks. Alternatively, we use per capita personal consumption from National Income as a proxy as well. $behavior_{it}$ represents the behavior proxy that reflects 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* corresponding to the three questions listed above. People who smoke, drink, and do not use preventive health service are considered to be less risk averse.

We also include household head's level of education, ethnicity, gender, occupation (skilled job or not), cadre (whether "Ganbu" or not) in $\mathbf{x_{it}}$ as control variables.

For people who smoke or drink, we expect to find that, in addition to a positive $\widehat{\gamma_2}$ the estimated coefficient $\widehat{\gamma_3}$ of the interactive term, *behavior* $*$ *aggshock*, is positive and significant. This indicates that for people with less risk aversion, their incomes correlate more positively with the aggregate shock. For people who utilized the preventive health care service, we expect to find that $\widehat{\gamma_3}$ is negative.

The estimated results are presented in Table 1 when aggregate shock is proxied by per capita real GDP. We use three estimation methods to estimate eq.(16), namely OLS, Fixed Effects and Random Effects panel estimations. Panel A presents the estimated coefficients of γ_1, γ_2 and γ_3 when smoking is used as a proxy for risk preference[20]. The estimated $\widehat{\gamma_2}$ are significantly positively different from zero. In addition, the key parameter that we focus on, the estimated $\widehat{\gamma_3}$, is significantly positive in all three estimations. This indicates that compared with people who do not smoke, incomes of those who smoke correlate more positively with the aggregate performance of the economy. This result is consistent with our expectation that for people with less risk aversion, their incomes correlate more positively with the aggregate risk.

[19]Table A1 in Appendix A provides summary statistics.

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

Similar results are obtained when drinking is used as a proxy for risk preference. In Panel B of Table 1, the estimated $\widehat{\gamma}_3$ is positive and significant. As a result, incomes of those who drink are correlated more positively with the aggregate shock, which is consistent with our expectation as well, as people who drink also tend to be less risk averse.

Panel C presents the results when risk preferences are proxied by use of preventive health care services. People who utilized the preventive health care services are considered to be less risk tolerant. The estimated $\widehat{\gamma}_3$ is expected to be significantly negative, which means that incomes of those who are more risk averse are correlated less positively with the aggregate shock. The estimated $\widehat{\gamma}_3$ is negative in all three cases, but is not significant. One possible reason 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 consumption from National Income Account. Similar to 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.[21].

4.2. Time preferences and household income

In the last section, it is shown that when people have heterogeneous time preferences, the estimated risk sharing parameter will be biased as well if the assumption of homogeneous time preference is maintained. This bias depends on how discrepancies of time preferences may leads to incomes of households to be correlate with the aggregate risk differently. If incomes correlate more positively with the aggregate risk for those who are less patient (discount future more heavily), 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 with the aggregate risk or not.

The natural question arises is how should we proxy for time preference. Fuchs (1982) conducted an experimental study and finds that 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 as relatively healthier, they tend to exhibit

[21]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 now shown here but 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 largely the same compared to those presented in Table 1 and Table 2. They are not presented but available upon request.

lower discount rate and be more patient[22]. As such, self-evaluated overall health could be used to proxy for time preference of a person.

Besides, Becker and Mulligan (1997) developed an endogenous time preference model which predicts that 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 by using PSID data of the U.S. households 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 both the self-evaluation of overall health at individual level and total assets at household level, plus income at household level. These 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[23]?
1. Excellent; 2. Very good; 3. Good; 4. Fair; 5. Poor

Those whose choices are smaller have higher self-rated health. Data on household total assets and income are also collected in two waves for the analysis[24]. We drop those

[22]Fuchs (1982) also found that smoking is significantly positively correlated with time preference. For people who smoke, they 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 cigarette 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 as well. 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 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) show by experiment that although subjects that 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.

[23]The options listed here are from 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 at "fair" in the two waves would choose 2 in 2010 but 4 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 3, or 4 or 5 in the 2010 survey, we reset them to 5 according to the closest option in 2012. For those who chose 2 we reset the answer to 4. This would help keep the choices between the two waves fairly consistent.

[24]CHNS provides a closely related question that also ask participants to evaluate their health condition. The question is: Right now, how would you describe your health compared to that of other people your

households that are headed by someone less than 20 years old or more than 65 years old. We also drop those households whose incomes are at the top or bottom 1%. This gives us 13,317 observations in two waves. Appendix A provides summary statistics.

We estimate the following specification:

$$\log(y_{it}) = \kappa_0 + \kappa_1 \cdot patience_{it} + \kappa_2 \cdot aggshock_t + \kappa_3 \cdot patience_{it} \times aggshock_t + \mathbf{x_{it}}\mathbf{\Phi} + \varsigma_{it} \quad (17)$$

where $patience_{it}$ denotes time preference of head of household i in year t and is proxied either by self-rated health of household's head or by household's total asset. Control variables $\mathbf{x_{it}}$ includes years of education, gender, ethnicity of household head, and a dummy indicating whether household head is party member. The estimated $\widehat{\kappa_3}$ is the key parameter of interest. If $patience_{it}$ is proxied by self-rated health, and if the estimated $\widehat{\kappa_3}$ is positive, it shows that for those whose self-rated health is poorer (higher value means poorer health and less patient), their incomes correlate more positively with the aggregate shock, and vice versa. This would cause the risk sharing coefficient to be estimated downward. 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 may cause the risk sharing coefficient to be biased downward (upward) accordingly.

Table 3 presents the regression results of eq. (17), 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 0.1690, while the FE and RE estimates are -0.5999 and -0.1256 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 see their incomes correlate differently with the aggregate shock is rather weak.

Panel B of Table 3 presents the estimation results when patience is proxied by household's total assets. The first column shows that the OLS estimated $\widehat{\kappa_3}$ is -0.0038. The FE and RE estimates of $\widehat{\kappa_3}$ are -0.0168 and -0.0072 respectively, both of which are statistically significantly different from zero. This indicates that for people who are wealthier, their incomes tend to correlate less positively with the aggregate risk. As wealthier people tend to be more patient, this results shows that for people with more patience, their income correlates less with the aggregate shock. As a results, the estimated risk sharing parameter in eq. (13) would be biased downward.

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age? The choices are: 1. Excellent; 2. Good; 3; Fair; 4.Poor. Data are available in all waves except 2009 and 2011 waves. In addition, CHNS provides only limited information on household's assets. Specifically, CHNS asks its participants if they owned or purchased any semi-durable goods or farm machine during the interview, and collects these information into household asset dataset. We use these two data to perform regression as well.

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

To sum up, the above results show that for households with more assets, their incomes correlates less positively with the aggregate shock. As wealthier people also tend to be more patient, this indicates that incomes of more patient people correlate less with the aggregate shock. This causes the risk sharing parameter in eq. (13) to be estimated with a downward bias. However, for household heads who have poorer self-rated health, this does not have any significant effect on how their households income may be correlated with the aggregate shock. This may be due to the possibility that, compared to households total assets, self-rated health is more likely to be measured with error. This measurement error may bias the estimated coefficient towards zero.

5. Robust risk sharing estimation results

Section 3 shows that if risk and time preferences are heterogenous and correlate with income processes, 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 do correlate more positively with the aggregate shock. And 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 preference heterogeneity.

Schulhofer-Wohl (2011) and Mazzocco and Saini (2012) provide two different ways to perform unbiased risk sharing tests in the presence of heterogeneous preferences. Schulhofer-Wohl (2011) estimated eq. (7) by grouping households' preferences η_i into the error term and treating them as nuisance parameters. Thus there is no need to estimate the household specific η_i. Schulhofer-Wohl (2011) then uses two techniques to estimate the risk sharing parameter θ in eq. (7). One is factor model estimation, the other is GMM estimation. The factor model nests both 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 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) then apply these two methods to estimate consumption risk sharing across U.S. 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 have 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. (7) using CHNS data and test full insurance at household level in China[25].

5.1. Factor model estimation results

Table 5 presents the results of factor model estimation using CHNS data on household real adult equivalent food consumption and real adult equivalent household income[26]. Household consumption here is measured by food consumption. CHNS provides a typical three-day consumption quantity on a variety of food items for each households. At community level prices of food items are provided. Combining these two pieces of information we compute food expenditures at household level. We have two measures of food expenditures at household level, namely food consumption in which a very small subset of vegetables and fruits are measured at either 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. In addition to these two food consumption measures, we compute two consumption measures which also include other nondurable consumptions provided by CHNS at household level[27]. In sum, we have four measures of household consumption, two of which are food consumption, the other two are nondurable consumption. In Table 5 we employ household per adult equivalent annual food consumption measured at the free market prices in which a small subset of food items were measured at the lowest free market prices.

Household income (excluding transfer) is measured as the sum of wage income, agricultural income, capital income, and business income. Transfer income, whether from public channel (eg. government transfer, or transfer from work unit) or private channel (eg. transfer between relatives and friends) is excluded. For those household members who work in collective/family farms and at the same time indicate that they are also in charge of that farm[28], their income from farming may be double counted from both wage

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

[26]Detailed discussion of data could be found in Appendix A.

[27]Other consumption expenditures mainly include housing services, utilities (electricity, fuel, etc.), health services, child care, etc.

[28]See CHNS Adult Survey 2001 question E10.

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. In order to empirically test whether transfer helps to facilitate household risk sharing, we also produce household income plus transfer, which is the income measure used by Mazzocco and Saini (2012). We thus have four measures of income, two without transfer and two with transfer. In Table 5 we use the household per adult equivalent annual income excluding transfer and in which wage income is used to measure income of those working in collective/family farming.

Because self-reported household income data may be subjected 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 that the potential bias caused by measurement error of income could 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 have an impact on consumption. Cochrane (1991) shows that if the social planner could freely transfer leisure across agents, individual's leisure does not have any impact on individual's consumption allocation[29]. As such, we use contemporaneous leisure as an instrument for income.

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 percent increase in income would cause a 0.3 percent increase in food consumption when aggregate shock is controlled for. It is also statistically significant at 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 U.S. households, which is 0.161 and is displayed at the bottom of Table 5, we observe that income changes have a smaller impact on consumption change for U.S. households

[29]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 problem occurs when Schulhofer-Wohl (2011) estimates risk sharing using U.S. household data.

than for Chinese ones, showing 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 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 risk preferences heterogeneity specification from the homogeneous preferences 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 U.S. 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 our previous expectations, as we find in Section 4.2 that, when incomes of people with less patience correlates more positively with the aggregate shock, this tend to bias downward the estimated risk sharing coefficient. However, the estimate is only marginally statistically significant at 10% level. When comparing this number with the estimate for the U.S., which is at 0.105, we find that: 1). When only time preferences heterogeneity is allowed, risk sharing coefficient for China is almost six folds of the U.S. estimate. This produces a more diverging picture of degree of risk sharing at 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 U.S., the opposite is implied 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 just 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 10% and 5% level according to the bootstrapped confidence intervals shown in the forth and fifth row of Column (4). As a result, **we are able to reject the hypothesis that 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 mid 1990s to early 2010s.

Table 6 presents the results when we use the alternative measure of food consumption and alternative measure of 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. 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 significantly at 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 10% level. When both 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 10% level. Using 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 is utilized. The results are very similar to those obtained in Table 5, which is reproduced at the bottom panel in Table 6. In addition, compared to the estimated risk sharing coefficients for U.S. households, the results obtained in Table 6 shows that neglecting preferences heterogeneity leads one to conclude that households in China has a lower insurance degree than U.S.. However, after the biases caused by preferences heterogeneity is adjusted, it turns out that Chinese households have full insurance that resembles their U.S. counterparts.

Since food consumption is only a fraction of household nondurable consumption, estimation based on food consumption may produce risk sharing estimate that serves as a lower bound of consumption insurance (Santaeulàlia-Llopis and Zheng, 2016; Blundell et al., 2008). Thus 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 $\widehat{\theta}$s under four different specifications are 0.3889, 0.2993, 0.6829 and 0.0723 respectively, all of which are somewhat larger to the estimated $\widehat{\theta}$s in Table 5 when household consumption is measured by food expenditures. However, this discrepancies are small, and Table 7 yields the same conclusions we obtain with 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 unit. 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 subsidies from the government, plus food and other gifts from work unit. Private transfer are payments and gift exchanges among friends and relatives. Since both social and private insurance channels could 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 $\widehat{\theta}$s are not closer to zero compared to that in Table 5 to 7, they now become less significantly different from zero. For example, the estimated $\widehat{\theta}$s in both Column (2) and (3) now become insignificantly different from zero at either 5% or 10% level, while they are significant at 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 enjoys 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 add to household income, while 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 have to be interpreted with 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 out 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 θ[30].

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

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

spectively.

Among the eight columns of Table 10, Columns with odd numbers display results when leisure is used as instrument for income only. Columns with even numbers display results when leisure is both controlled for as an independent variable and used as instrument for income and for itself. This helps us to take into account the nonseparability between consumption and leisure. Column (1) shows that the estimated risk sharing coefficient is 0.1846 and is insignificantly different from zero at 5% level. This number is smaller than the estimated coefficient produced in Table 5 by factor estimation (0.3125). Column (3) and (5) shows that when time or risk preferences are allowed to differ across households separately, the estimates become 0.6007 and 0.2353, respectively. Both are statistically significant at 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[31]. 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 both time and risk preferences are heterogeneous. For all specifications except for Column (8), the overidentifying restrictions are never rejected[32].

The bottom row displays the corresponding estimation for the U.S. 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 happens 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

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

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

(1), which is similar to the results from U.S. households. In general, after taking into account time and risk preferences heterogeneity, column (7) and (8) shows consistent results with those obtained from factor estimation, that is, Chinese households have full insurance and this is similar to that of U.S. 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[33].

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 remains qualitatively similar compared to Table 10.

In order to gauge the effect of transfer income on households 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.

5.3. Summary and discussion

The above estimation results based on factor model show that allowing risk preferences heterogeneity tends to reduce the magnitude of estimated risk sharing coefficient, while both factor model and GMM model shows that allowing time preferences heterogeneity tends to increase it. When both risk and time preferences are assumed to differ across households, both factor model and GMM model produces an estimated $\widehat{\theta}$ that is insignificantly different from zero.

The differences in estimation results mainly come from two sources. First, factor model and GMM model have different set-ups. The GMM test analyzes how consumption responds to changes in income from one wave to the next, while the factor test analyzes 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, households consumption growth is uncorrelated with contemporaneous income growth. However, over longer time horizon, household consumption would track household income more closely when risk sharing is incomplete (Hayashi et al., 1996). As a result, the factor model, due to its fix effects transformation, may detect more failures of full risk sharing. That is why factor

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

models produces at least as many significantly positive $\widehat{\theta}$s as GMM test. Second, GMM test allows us to control for leisure as a separate independent variable, while this is not possible in factor model.

Both factor model and GMM method produce estimates of risk sharing coefficient that is insignificantly different from zero under heterogeneous risk and time preferences specifications, indicating of full insurance at households level in China. Compared to homogeneous preferences specifications, the factor model shows that the difference between the "both heterogeneous" case and the "both homogeneous" case is statistically significant at 5% or 10% level. Coupled with the institutional changes occurred in China during mid 1990s and early 2010s, it provides suggestive evidence that those reforms, particularly those labor 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 labor mobility and job choices were quite limited for both rural and urban residents. Back in the 1980s or before, even if people have different preferences, there is not much space for them to reveal this differences through their job market choices. However, this is no more the case after mid 1990s. As a result, when one performs risk sharing test in China, the probability to generate biased estimates of risk sharing coefficients becomes much higher when one utilizes data after mid 1990s.

By comparing the estimated effects of income on consumption we obtained for households in China with U.S. households in Schulhofer-Wohl (2011), we find that the degree of risk sharing across households in China resembles that in the U.S.. However, an important difference between Chinese and U.S. households also emerges, which is that the income of less patience households in China correlates more positively with the aggregate shock, while it is the opposite in the U.S..

Our estimated risk sharing parameter could also be compared to a few papers that test risk sharing across China at different levels. We summarize them in Table 14. Most of them utilize aggregated provincial or prefectural 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 to 0.108, which tend to be larger than our results in factor model under the specification of both 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 didn't deal with the

[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.

potential measurement error problem in household income. Since it is very likely that in survey data, income might have been measured with error, this would cause a downward bias in the estimated risk sharing coefficient. Third, their data span is different from ours. Compared to our data, they utilized three more waves, 1989, 1991 and 1993 in CHNS, and they didn't use the most recent 2011 wave. Finally, in their specification, leisure is assumed to be separable from consumption, while in our GMM estimation, we take into account the nonseparability between consumption and leisure.

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.

Finally, our results show that transfer income, whether it is public or private transfer, when included into income, also produces an estimated risk sharing coefficient that shows full insurance at households level in China. This result has important policy implications, as it shows that at least public transfers do not have any negative effect on risk sharing among households.

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 that 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 bear more aggregate risk of the economy. In addition, neglecting time preferences heterogeneity may bias the risk sharing parameter either upward or downward, depending on whether people with more patience bear more or less of the aggregate risk of the economy.

By utilizing two household level survey data, 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 ordinary Chinese through a series of institutional reforms occurred during mid 1990s and early 2010s. As such, the effects of risk and time preferences heterogeneity on the estimated risk sharing coefficient are of opposite directions, with the formal to cause an upward bias, while the latter a downward bias. This finding distinguishes Chinese households from their U.S. counterparts, as in U.S., households with more patience bear more aggregate risk of the economy.

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 standard risk sharing test in which preferences are assumed homogeneous produces an estimated risk sharing coefficient of around 0.3, which is also significantly different from zero. When risk preferences heterogeneity is allowed only, this number reduces to around 0.28 and remain significant. When time preferences heterogeneity is present only, it increases to around 0.67. When both risk and time preferences are present, the estimate reduces to 0.03 and becomes insignificantly from zero. It is also statistically significantly different from the estimate under the homogeneous preferences specification. In summary, it shows that the degree of consumption risk sharing across households in China is complete. Further comparison of our results with that of Schulhofer-Wohl (2011) shows that households risk sharing in China is similar to that across households in the U.S.. We provide suggestive evidence to show that institutional reforms during mid 1990s to early 2010s, which enabled Chinese people with more freedom in their labor market choices, may have contributed to this improvement of risk sharing across households in China when preferences heterogeneity is taken into account.

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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(γ_1)	-3.2120^{***c}	-3.3332***	-3.2007***
	(0.4724)[b]	(0.6406)	(0.5883)
aggshock(γ_2)	1.3876***	1.3569***	1.3649***
	(0.0745)	(0.1226)	(0.1148)
smoke * aggshock(γ_3)	0.7533***	0.7789***	0.7484***
	(0.1138)	(0.1540)	(0.1414)
Panel B: Risk preferences proxied by drinking[a]			
drink(γ_1)	-4.1692***	-3.5705***	-3.8511***
	(0.4661)	(0.6199)	(0.5601)
aggshock(γ_2)	1.2523***	1.2974***	1.2631***
	(1.0217)	(1.1232)	(0.1142)
drink * aggshock(γ_3)	1.0046***	0.8462***	0.9223***
	(0.1122)	(0.1478)	(0.1340)
Panel C: Risk preferences proxied by use of preventive health care services[a]			
prvhcare(γ_1)	1.8901	2.0780	2.4093
	(1.8514)	(1.6195)	(1.4926)
aggshock(γ_2)	1.7073***	1.7087***	1.6941***
	(0.0580)	(0.1048)	(0.0982)
prvhcare * aggshock(γ_3)	-0.3913	-0.5020	-0.5454
	(0.4381)	(0.3843)	(0.3559)

[a] Data used here are collected from 1997, 2000, 2004, 2006, 2009 and 2011 waves of China Health and Nutrition Survey (CHNS). Smoking indicates whether or not household's head smokes; Drinking indicates whether or not household's head drinks; Use of preventive health service indicates whether or not household's head utilized 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, years of education, occupation type, ethnicity, whether cadre or not, plus a constant. The estimated coefficients are not shown here but 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(γ_1)	-3.8399***[c]	-3.9667***	-3.8126***
	(0.5818)[b]	(0.7946)	(0.7299)
aggshock(γ_2)	1.9242***	1.8958***	1.8994***
	(1.0215)	(0.1659)	(0.1556)
smoke * aggshock(γ_3)	1.0002***	1.0303***	0.9907***
	(0.1549)	(0.2113)	(0.1939)
Panel B: Risk preferences proxied by drinking[a]			
drink(γ_1)	-5.0372***	-4.2636***	-4.6277***
	(0.5741)	(0.7623)	(0.6908)
aggshock(γ_2)	1.7398***	1.8150***	1.7607***
	(0.1055)	(0.1665)	(0.1546)
drink * aggshock(γ_3)	1.3419***	1.1204***	1.2266***
	(0.1528)	(0.2013)	(0.1829)
Panel C: Risk preferences proxied by use of preventive health care services[a]			
prvhcare(γ_1)	2.4565	2.9259	3.2284
	(2.2255)	(1.9573)	(1.8074)
aggshock(γ_2)	2.3526***	2.3661***	2.3397***
	(0.0790)	(0.1422)	(0.1332)
prvhcare * aggshock(γ_3)	-0.5823	-0.7819	-0.8198
	(0.5843)	(0.5150)	(0.4775)

[a] Data used here are collected from 1997, 2000, 2004, 2006, 2009 and 2011 waves of China Health and Nutrition Survey (CHNS). Smoking indicates whether or not household's head smokes; Drinking indicates whether or not household's head drinks; Use of preventive health service indicates whether or not household's head utilized 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, years of education, occupation type, ethnicity, whether cadre or not, plus a constant. The estimated coefficients are not shown here but available upon request.

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)	-0.6157	2.6668	0.6547
	(1.9876)[b]	(2.3760)	(0.8317)
aggshock (κ_2)	2.7683***	5.8859**	2.8271***
	(0.3721)	(1.7888)	(0.5137)
self-rated health * aggshock (κ_3)	0.1690	-0.5999	-0.1256
	(0.4562)	(0.5451)	(0.4902)
Panel B: Time preferences proxied by household total assets			
total assets (κ_1)	0.0193	0.0753**	0.0339*
	(0.0139)	(0.0253)	(0.0152)
aggshock (κ_2)	3.0488***	6.1092***	3.0521***
	(0.2790)	(1.7267)	(0.4861)
total assets * aggshock (κ_3)	-0.0038	-0.0168**	-0.0072*
	(0.0032)	(0.0057)	(0.0034)

[a] Data used here are collected from 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 gender, years of education, ethnicity, whether a communist party member or not, plus a constant. The estimated coefficients are not shown here but 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)	-0.7252	3.0555	0.7361
	(2.2832)	(2.7292)	(2.4485)
aggshockc2 (κ_2)	3.5442***	7.5356**	3.6195***
	(0.4752)	(2.2902)	(0.6577)
self-rated health*aggshock (κ_3)	0.2164	-0.7680	-0.1609
	(0.5840)	(0.6979)	(0.6276)
Panel 2: Time preferences proxied by household total asset			
total asset (κ_1)	0.0217	0.0862**	0.0386*
	(0.0160)	(0.0290)	(0.0174)
aggshockc2 (κ_2)	3.9033***	7.8215***	3.9076***
	(0.3573)	(2.2107)	(0.6223)
total asset*aggshock (κ_3)	-0.0048	-0.0215**	-0.0092*
	(0.0041)	(0.0074)	(0.0044)

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])

	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])

	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])

	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])

	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])

	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: 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 income 1980-2004	Preferences homogoeneity	OLS	0.09 ~ 0.29
Curtis and Mark (2010)	Provincial level consumption and output data 1954-2004	Preferences homogoeneity	OLS	0.50 ~ 0.67
Du et al. (2011)	Provincial level consumption and output data 1990-2007	Preferences homogoeneity	Fixed effects	0.674 ~ 0.709
Chan et al. (2014)	Provincial level consumption and output data 1952-2008	Preferences homogoeneity	Fixed effects and random effects	-0.020 ~ 0.7107
Ho et al. (2015)	prefectural-level city retail sales and output data 1990-2010	Preferences homogoeneity	OLS	0.36 ~ 0.41
Santaeulàlia-Llopis and Zheng (2016)	CHNS households level consumption and income data 1989-2009	Preferences homogoeneity	OLS	0.041 ~ 0.108

Appendix A. Data compilation

Our empirical investigation on risk sharing at household level in China is based on data from two household surveys, namely China Health and Nutrition Survey (CHNS) and China Family Panel Survey (CFPS). Depending on data availability and time span, we use the former to test consumption risk sharing at household level in China under different specifications of preference heterogeneity, and we use both to test whether preference heterogeneity matters for obtaining an unbiased risk sharing coefficient.

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 CHNS does not provide sufficient information for us to compute household consumption. In each wave, CHNS roughly selects around 200 primary sample units (PSU) in 9 provinces in China, they are Guangxi, Guizhou, Henan, Hubei, Hunan, Jiangsu, Shandong, Heilongjiang and Liaoning[35]. Among those selected PSUs, roughtly one third are from urban area and the other two thirds from rural area. Although CHNS is not designed as a representative household level survey data in China, it is nonetheless one of longest available household level survey data in China.

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

Appendix A.1.1. Household income and leisure

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

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

where $hhinc_{i,t}$ is household income net of transfer, or just household income for short. $wage_{i,t}$ 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.

[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 these data, while differs from their methods in a few aspects. We refer readers to Santaeulàlia-Llopis and Zheng (2016) for detailed discussion of CHNS survey data.

1. **Household labor earnings and leisure**. CHNS records household income from four main sources, labor earnings, agricultural income, business income, and capital income. Labor earnings for all working individuals across waves 1997 to 2011 are extracted from the file *wages_00*. Labor earnings for an individual are defines 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 labor earnings using $c8 * c3 + i19$, where $c3$ is the number of months that an individual has worked on this occupation. Household labor earnings are the sum of the labor 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 thus 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 labor earnings is that, wage/salary, and agricultural labor income from collective entities at 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/poutry raising) as their primary or secondary occupation, apart from being asked about the salaries they earn from these occupations, they are asked again in details about their agricultural income from these agricultural activities[37]. In order not to double count the labor earnings for those who work at collective agricultural entities, we either take their wage/salary from their primary or secondary occupation as their labor earnings, or we take their agricultural income from the agricultural activities as their labor earnings. Summing up labor earnings of individual members within each household, this gives us two measures of labor earnings at household level. The way we 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 both household and individual level. At household level, agricultural income is collected from five activities, farming, gardening, livestock/poutry, 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

[37] In the adult questionnaire, wage/salary data are collected from all adults who work. Agricultural income data are collected from all adults. For adults who reported themselves working at collective entities in agricultural sector, their labor earnings could have been collected twice. However, for those adults who didn't report themselves as working, their labor earnings from agricultural activities at collective entities may be collected just once. We believe that the number of adults who work at collective entities but did not report themselves as working is rather limited.

who work at the collective farming, livestock/poutry, 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 recorde for collective fishing, and $g9$ is value of fish recorded from collective farm last year. Individual livesthock/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 labor 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. Sum this income across members of a household, we obtain household level business 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.

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:

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

where $transfer_{i,t}$ is the sum of all types of transfers received by household i at time t, $sub^{wu}_{i,t}$ and $sub^{wu}_{i,t}$ 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. $transf^{pri}_{it}$ is private transfers received by household members from relatives and friends. One of the difference from our measure of household transfer income and Santaeulàlia-Llopis and Zheng (2016)'s measure is that we do not include food coupon. This is because our sample starts from wave 1997, and food coupon 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.

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 summarized 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 prices at two different

[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).

level: highest price and lowest price. We use free market price to compute household food expenditure. In order 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 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 price 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 consumption 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 ever smoked ($u25$), the second is whether a person ever drank bear or alcohol last year ($u40$), the third is whether a person participated in preventive

[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.

[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.

health service during the last four weeks at the time of interview (*m*47). *u*25 and *u*40 are from the file *pexam_00*, *m*47 is from the file *hlth_00*.

We collect one variable that is proxy for household head's time preference, which is self-reported current health condition (self-rated health)(*u*48*a*). 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.

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 deflate the nominal values to real values. We use *index_new* provided in the data file *c*12*hhinc*, 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% incomes, and the top and bottom 1% consumptions. Table A1 summarizes the data we compiled from CHNS.

Appendix A.2. Data from CFPS

We use data from China Family Panel Survey (CFPS) to test the relevance of household risk and time preferences on estimating risk sharing coefficient unbiasedly[42]. In particular, we collect household income and total assets from family survey, and household head's smoke, drink and self-rated health status from adult survey. We use the 2010 and 2012 waves, and select households with head aged between 20 and 65. Then we trim the top and bottom 1% incomes. Table A2 provides the summary statistics.

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

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[43].

[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.

[43]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 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	

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	

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

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

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

GMM tests are based on the following moment condition:

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

where v_{is} represents the instrumental variable, e_{it} is the error term in eq. (7) or (8). 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 $\eta_i = 1$ 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[44]:

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

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:

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

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

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:

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

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

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

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

where s and q depend on time lag between two adjacent waves. For example, for wave 2011, if we take a quasi-differecing, we obtain:

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

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:

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

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:

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

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.