Household Finance in China*

Russell Cooper[†] and Guozhong Zhu[‡]

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Abstract

This paper studies household finance in China, focusing on the high savings rate, the low participation rate in the stock market, and the low stock share in household portfolios. These salient features are studied in a lifecycle model in which households receive both income and medical expense shocks. The structural estimation explicitly takes into account important regime changes in China, such as the re-opening of the stock market around 1990, the privatization of housing markets around 2000 and the completion of labor market reforms around 2000 that changed household income processes. The paper also compares household finance patterns in China to those in the US, and shows that between-country differences in financial choices are driven by both institutional reasons (e.g. higher entry cost into the stock market and lower consumption floor in China) and preferences (e.g. higher discount factors of the Chinese).

1 Introduction

Chinese households tend to save more than their US counterparts. As a result, the average wealth-to-income ratio in China is 14.67 in China compared with 4.46 in the US.[1] This paper studies the wealth accumulation and portfolio composition of Chinese households, and compares them with the financial decisions of the US households.

The analysis goes beyond the traditional focus on the high savings rate in China to study in detail the following features, over the lifecycle, of Chinese household financial choices: (i) low stock market participation rates, (ii) low shares of wealth in stocks conditional on participation, and (iii) high wealth-to-income ratios. Relative to the US household finance patterns, the low participation rates and high wealth-to-income ratios in China are particularly striking, as shown in Table 1. A number of contributing factors are potentially important, such as the major regime changes experienced by the Chinese households (cohort effects), the underdeveloped equity market and the

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†Department of Economics, the Pennsylvania State University and NBER, russellcoop@gmail.com

‡School of Business, University of Alberta, guozhong@ualberta.ca

[1] The wealth-income ratio in China is calculated from the 2011 wave of China Household Finance Survey, the ratio in the US is based on seven waves of Surveys of Consumer Finance between 1989-2007. In the calculation households with zero income are excluded.

labor market featuring high income uncertainty and weak social insurance in China (institutional reasons), and the different preferences of Chinese households compared to those of the US households. This paper studies the quantitative importance of these factors using a model of household optimal decisions over the lifecycle.

The model is estimated via Simulated Method of Moments (the SMM hereafter), exploiting the variations of household finance patterns by education attainment and age. The estimation is challenging for a few reasons. First, substantial cohort effects exist. Chinese households have experienced important regime changes at different stages in their lives. For example, the cohort aged 40 in a 2011 survey were college-age when the stock market in China re-opened around 1990 so their financial decisions should be little affected by this regime change. But they should be strongly affected by the housing reform around 2000 when they were 30, an age of home purchases. On the other hand, the cohort aged 65 in 2011 should be less affected by the housing reform because they were retiring at the time of reform.[2] But their financial decisions should be strongly affected by the re-opening of the stock market around 1990 when they were 45, an age when portfolio investment is an important decision. Second, the currently available data only span a few years. As a matter of fact, there is only one single cross section of household data publicly available for China with enough details and coverage to study financial choices – the 2011 wave of China Household Finance Survey (CHFS hereafter).[3] This nullifies the standard way of using cohort dummies in long repeated cross sectional data.

A novel element of our analysis is to design an estimation strategy to cope with the cohort effects resulting from multiple regime changes in China using a single cross section of data. Specifically, for different cohorts in the 2011 CHFS, we solve their lifecycle optimization problems, taking the regime changes that occurred at cohort-specific ages explicitly into account. The resulting optimal decision rules and the simulated lifecycle financial decisions are cohort specific. We pool the simulated data for various cohorts together to calculate their household finance moments in 2011 that are comparable to the data counterparts in the sense that both the model moments and data moments summarize the cohort-specific impacts of the regime changes. This way the cohort effects are incorporated into the model and thus do not bias our estimation results.

Chinese household finance patterns vary considerably with education, income, sector of employment and region (urban versus rural). In the structural estimation we focus on the heterogeneity by education for a number of reasons. First, the college premium has changed significantly over time and the changes are taken into account when the model admits heterogeneity in education attainment. Second, the results are compared with a parallel study on the US household financial choices, i.e. Cooper and Zhu (2016), where heterogeneity in education is also explicit. Third, education is highly correlated with the other dimensions of heterogeneity. Better educated households typically live in urban area, have higher income, and have a high employment percentage in the state sector. Nevertheless we also carry out and report structural estimations based on heterogeneity in region (rural versus urban) or in sector of employment (non-state versus state).

Using the estimated model, we study the quantitative effects of regime changes in China on household financial choices. Counterfactual analysis reveals that the structural changes in labor income process and the housing reform

[2] Statutory retirement age is 50 for female workers and 60 for male workers in China.
[3] CHFS conducted several follow-up surveys since 2011, but only the 2011 wave is publicly available.

have large impacts. Had households in the 2011 survey not experienced the earlier labor market condition with low income uncertainty, their wealth-income ratio would be about 20% higher, and the stock market participation rate would almost double. Without the privatization of housing markets and the ensuing house price run-ups, the wealth-income ratio would be 25% lower on average. Overall, the paper predicts that in the completely new regime households will save even more, have much higher participation rates in the stock market, and have higher stock shares in total wealth.

To understand the large difference between China and the US in household finance patterns, we summarize the country-specific characteristics by three sets of parameters, related to (i) household preferences, (ii) the financial market, and (iii) the labor market, respectively. These parameters are estimated either directly from the data or indirectly via the SMM. We estimate a parallel US model and obtain these three sets of parameters for US households in the US markets, then conduct experiments that apply one country's parameters on another. In the experiment where households with Chinese preferences work in the US labor market and invest in the US financial market, these households have an average wealth-income ratio that is three time larger than the US household observed in the US data. The stock market participation rates and stock share in total wealth are also higher than the US households. In the case that the Chinese households works in China, but make investment in the US financial market, their wealth-income ratio is even higher, reaching 9.6 times of the US households. Stock market participation rate is near 100%, but the stock share in total wealth is slightly lower than the US households, partly reflecting lower risk-taking due to the high income uncertainty and weak social insurance in China. On the other hand, for households with the US preferences that work and invest in China, their stock market participation rate is near zero, and their wealth-income ratio is only 30% of the Chinese counterparts in China. Further, if these US households are in the US labor market, but only invest in the Chinese financial market, none of them participate in the stock market and their average wealth-income ratio is only 7.3% of the Chinese counterparts in China. Together, these experiments show that preferences play a more important role in the cross-country difference in wealth accumulation, but conditions in either the labor market or the financial market are also critical, especially in explaining the low stock market participation rate in China.

The rest of the paper is organized as follows. Section 2 presents data facts about household finance in China and compares them with the US household finance patterns. Section 3 introduces the structural model where the optimization problem of households and the key market frictions are laid out. Section 4 discusses the estimation strategy. Section 5 reports estimation results both from the baseline case and from the robustness analysis. Section 6 studies the impact of the regime change on household finance patterns and wealth distribution in China. Section 7 experiments with the factors contributing to the large difference between China and the US. Section 8 concludes.

2 Data Facts

This section presents facts about household financial decisions, for both China and the US.[4] As household decisions are driven, in part, by the processes for income and medical expenses, these are presented as well. For both China

[4]Further details for China are in the Appendix. Cooper and Zhu (2016) provides details for the US and calculation of these moments.

Table 1: Household Facts by Education and Age

	China				US			
	Pre-retirement		Post-retirement		Pre-retirement		Post-retirement	
	low-edu	high-edu	low-edu	high-edu	low-edu	high-edu	low-edu	high-edu
part.	0.075	0.337	0.070	0.229	0.174	0.550	0.209	0.646
	(0.01)	(0.012)	(0.011)	(0.021)	(0.01)	(0.004)	(0.011)	(0.004)
share	0.435	0.502	0.511	0.515	0.522	0.572	0.444	0.551
	(0.039)	(0.024)	(0.046)	(0.043)	(0.021)	(0.003)	(0.02)	(0.003)
share(h)	0.126	0.135	0.085	0.172	0.258	0.379	0.232	0.364
	(0.023)	(0.014)	(0.026)	(0.025)	(0.025)	(0.015)	(0.015)	(0.003)
W/I	1.580	2.038	1.363	2.473	0.071	0.377	0.500	2.805
	(0.199)	(0.235)	(0.217)	(0.398)	(0.039)	(0.04)	(0.158)	(0.078)
W/I(h)	11.169	17.137	14.502	17.756	0.313	1.260	3.867	6.454
	(1.112)	(1.308)	(1.206)	(2.216)	(0.124)	(0.107)	(0.431)	(0.144)

This table displays the participation rate (direct and indirect stock holdings), the share of stocks (for participants), the median wealth income ratio (W/I) for Chinese and US households by age and education group. Data for China is from the CHFS. Data for the US is from the SCF. Households whose heads have at least high school diploma are defined as high education households which account for 89% of the US households in SCF sample and 36.4% of the Chinese households in CHFS.

and the US, the processes and financial decisions are presented for two educational attainment levels: (i) high school and below (low-edu) and (ii) beyond high school (high-edu).[5]

2.1 Patterns of Household Finance: China

The patterns of household financial decisions are shown in the left panel of Table 1. The moments for China are computed from the Chinese Household Financial Survey conducted in 2011 and released in 2012, described in the Appendix.

Detailed information about the CHFS is available at `http://www.chfsdata.org/`. The intent of the survey was to gather household finance information from the individuals with most knowledge about their household's financial status. For each household in the sample, the survey identifies a respondent which is defined as the member who knows best about a household's financial situation.[6] For 86.22% of the households in the survey, the respondents and their spouses make decisions regarding stock market investment.[7]

We focus on three dimensions of household financial decisions: (i) the stock market participation rate, (ii) the share of stock in the household portfolio conditional on participating in asset markets, and (iii) the median wealth to income ratio.[8] A household is considered a stock market participant if it holds stocks either directly or indirectly or both.[9] Through the paper, the calculation of wealth-to-income ratio is based on total family income which

[5]In CHFS2011, only 0.9% of the individuals have post-graduate education and only 7.4% have bachelor's degrees. So a finer breakdown by education attainment is not feasible for Chinese households. Thus the estimation results are not directly comparable to those reported in Cooper and Zhu (2016) for the US households.

[6]See question [A1013] in the questionnaire.

[7]This is calculated from question [D3112] in the survey.

[8]The median is chosen to avoid outliers in the wealth distribution.

[9]Direct stockholding information is provided in questions [D3101] and [D3103] of the survey. Indirect holding is through mutual funds that invest mainly in the equity market, with related information obtained in answers to questions [D5104] and [D5107].

includes the sum of family members' labor income plus transfer from non-family members and the government.

The table presents two measures of these last two ratios. One, labeled 'share(h)' is the stock share relative to the sum of financial and housing wealth while 'share' is just stocks relative to financial wealth. Likewise, 'W/I(h)', includes housing in wealth. The other measure, 'W/I' excludes housing wealth, thus focusing on financial wealth.

Since we have only one cross section of survey data, it is not feasible to isolate lifecycle profiles from either year effect or cohort effect. Instead we present two components of the lifecycle for each household financial decision: before and after retirement. These two components are also contaminated by cohort or housing effects which will be addressed in detail in the estimation.

As is well appreciated, the wealth to income ratio is higher in China than in the US for various representations of the data. For example, the median wealth to income ratio for low education workers is about 10 times higher than in the US when housing is included in wealth. The wealth to income ratio is also higher for post-retirement households though the differences across countries by education group are not as stark. Once housing is excluded from wealth, the wealth to income ratios naturally are lower. It is noteworthy that housing is a much more important component of wealth for Chinese households, particularly the less educated. Table 1 makes clear that the manner of wealth accumulation also differs across these countries. This difference is a key part of our analysis.

The asset market participation rate (both direct and indirect holdings) is much lower in China. This is the case for all age and education groups. In China, as in the US, the participation rises with education attainment but, unlike the US, it is lower for retirees.

Table 2: by Total Family Income Group

	part.	share	W/I	share(h)	W/I(h)	home ownership rate	age	fraction of high-edu
lower 10%	0.029	0.375	3.70	0.100	52.83	0.86	55.00	0.13
	(0.006)	(0.012)	(0.59)	(0.005)	(7.04)	(0.01)	(0.52)	(0.01)
median	0.088	0.608	0.70	0.118	7.58	0.85	49.11	0.31
	(0.028)	(0.034)	(0.12)	(0.013)	(1.3)	(0.04)	(1.14)	(0.05)
top 10%	0.425	0.490	1.28	0.117	8.67	0.79	44.14	0.71
	(0.019)	(0.011)	(0.09)	(0.006)	(0.38)	(0.02)	(0.45)	(0.02)
top 1%	0.500	0.490	1.33	0.178	4.07	0.69	42.53	0.76
	(0.059)	(0.036)	(0.36)	(0.025)	(0.55)	(0.05)	(1.24)	(0.05)

This table displays household choices by income groups in China. Standard errors are reported in parenthesis. The statistics of median income households are based on 100 households in the sample whose income is closest to sample median income

The stock share of US households, defined as the share of stock in total financial assets for participants, is almost double that of Chinese households. For both countries, the stock share rises with education, though this effect is barely evident for pre-retirement Chinese households.

Table 2 shows household financial decisions in China by family income. Clearly the participation rate rises with the level of family income. Households with the bottom 10 percentile income have significantly higher wealth-income ratio than the other groups, which is partly caused by the high degree of income uncertainty in China –

the low income household observed in the survey could have had high income earlier. In addition, the education premium was much lower pre-2000, so a low income household in the 2011 CHFS may have been high income one in 1990s and accumulated a large stock of wealth.

There are also potentially interesting differences conditioning on the sector of employment. In particular, households with employment in the public sector may have more stable income and higher benefits.[10] Table 3 shows financial decisions for public and private sector workers. The wealth to income ratio is actually higher for public sector workers as is the participation rate.[11] These workers tend, on average, to have higher education attainment compare to private sector workers. This translates into a higher participation rate as well as a higher wealth to income ratio and more homeownership.

Table 3: Sectors and Regions

	part.	share	W/I	share(h)	W/I(h)	home owner-ship rate	age	fraction of high-ed
public	0.316	0.514	1.22	0.129	11.17	0.86	42.25	0.81
	(0.014)	(0.01)	(0.09)	(0.006)	(0.57)	(0.01)	(0.29)	(0.01)
private	0.145	0.498	0.76	0.124	10.03	0.76	41.73	0.42
	(0.011)	(0.009)	(0.05)	(0.006)	(0.56)	(0.01)	(0.3)	(0.02)
urban	0.185	0.512	1.64	0.125	19.02	0.81	49.10	0.50
	(0.006)	(0.005)	(0.11)	(0.003)	(1.06)	(0.01)	(0.21)	(0.01)
rural	0.027	0.468	0.72	0.118	9.43	0.94	52.25	0.14
	(0.003)	(0.006)	(0.04)	(0.003)	(1.03)	(0.004)	(0.23)	(0.01)

This table displays household finance by employment sector. Public sector employees include those employed by the government and state-owned enterprises. Private sector includes workers in rural area, collectively owned firms, private firms and firms with joint ownership with foreigners.

Another potentially important distinction is between urban and rural households. The bottom panel of Table 3 summarizes household financial decisions by region. The participation rate is much higher in the urban sector as is the wealth to income ratio. The homeownership rate is higher in the rural sector. Further, the fraction of high education households is significantly higher in the urban sector.

2.2 Patterns of Household Finance: US

The US household finance patterns are estimated from seven waves of Survey of Consumer Finance between 1989 and 2007. The right panel of Table 1 shows the US statistics without any control for year or housing effects. To control for these effects and isolate the lifecycle patterns, we regress each of the three household financial decision on a constant, age, age-squared, year dummies and home ownership dummy. The predicted lifecycle profiles by education attainment are shown in Figure 1. There is a distinct ordering by education: participation, stock share and wealth-income ratio all increase with education. Further, there are clear life cycle effects with participation and the stock share both exhibiting hump-shaped patterns.

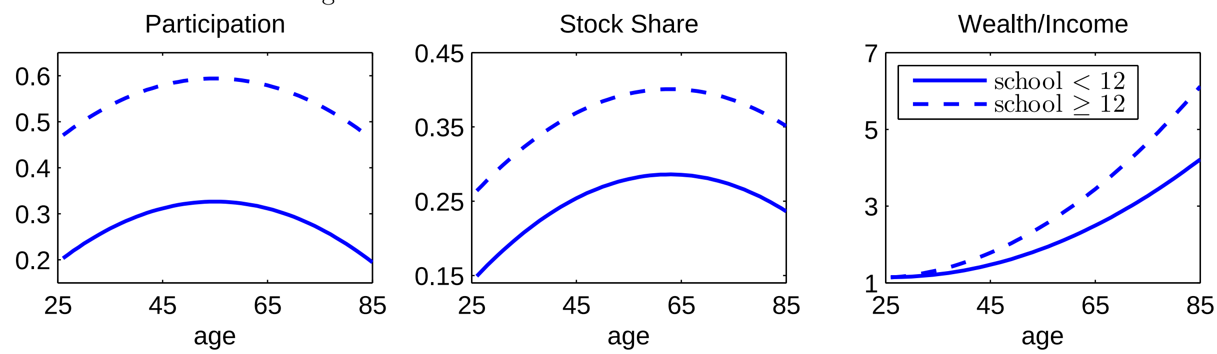
[10] See the discussion of this point and related references in He, Huang, Liu, and Zhu (2014).

[11] Only 28.6% of respondents in the sample provide valid information on their sector of employment, among them 17.9% are rural residents.

One of the challenges in matching the US data is the rising wealth to income ratio over the life cycle. Though income falls at the end of the life cycle, there is also an increase in wealth. Cooper and Zhu (2016) argue that this is largely due to a bequest motive rather than precautionary saving for medical expense risk.

For the moments in Table 1, this increasing wealth to income ratio found in the US data is not apparent for China. Looking at older cohorts in the Chinese data, we find that the wealth-income ratio for those aged 60-69, 70-79 and 80-89 are 10.97, 11.81 and 12.80 respectively in the CHFS data. We return to a discussion of matching these additional features of the data in section 7.

Figure 1: US: Profiles of Household Financial Decisions



These profiles show the age dependence of household financial decisions. The regressions underlying these figures are explained below. For the figures labelled 'housing', home equity is included in wealth.

3 Household Dynamic Optimization

The dynamic optimization model for the household is a modified version of that presented in Cooper and Zhu (2016). The parameters of this model are estimated using a SMM approach for both the US and China. The model emphasizes two key discrete choices of the household: participation in the stock market and adjustment of the portfolio. Housing asset is bundled with risk-free and low-return asset to form a composite asset called a bond which is assumed to be risk-free. Section 4.2.3 reports stochastic property of housing return which justifies this assumption.

A household lives for T periods, working for the first $T^r < T$ periods of life. During the working phase of life, households earn stochastic income. Also, during retirement, the household receives deterministic income, but faces out of pocket medical expenses that are stochastic. To be clear, these exogenous processes differ across the two countries and are, in part, a source of difference in financial choices.

In the presentation of the household optimization problem, there is no explicit index of education nor any indicator of the country. It is implicit that a household from country i with education e will face the stochastic processes for income and medical expenses that are estimated for that education group in that particular country. The same applies for other splits of the sample in China, such as the rural households and urban households that we study separately.

3.1 Participant

Let Ω represent the current state of the household. This includes the current income of the household as well as its holdings of financial assets and its current medical expenses. That is, $\Omega = (y, m, A)$, where $A = (A^b, A^s)$ summarizes the current value of the holdings of bonds and stocks respectively.[12]

A household that is currently holding stocks, i.e. is a participant, chooses between three alternatives: (i) portfolio adjustment, (ii) no adjustment and (iii) exiting the assets markets by selling all stocks. This choice is given:

$$v_t(\Omega) = \max\{v_t^a(\Omega), v_t^n(\Omega), v_t^x(\Omega)\} \tag{1}$$

for all Ω.

If the household chooses to adjust, it chooses stock and bonds solve:

$$v_t^a(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b, A^{s\prime} \geq 0} u(c) + \beta E_{y',m'|y,m} \left\{ (1-\nu_{t+1}) v_{t+1}(\Omega') + \nu_{t+1} B(R^b A^{b'} + R^{s'} A^{s'}) \right\}$$

$s.t.$

$$\begin{aligned} c &= y + TR - m + \textstyle\sum_{i=b,s} R^i A^i - \sum_{i=b,s} A^{i'} - F \\ TR &= \max\{0, \underline{c} - (y + \textstyle\sum_{i=b,s} R^i A^i - m)\}. \end{aligned} \tag{2}$$

where $\underline{A}^b$ is the lower-bound of bond holding. The lower bound of stock holding is zero so short sales of stocks is not allowed. In the quantitative analysis, we find that treating A_b as an additional free parameter does not improve the fit of the model. Therefore $A_b = 0$ is imposed.

Here ν_{t+1} is the survival probability, which depends on both age and, implicitly, the education of the agent. There is a transfer allowed from the government to the household to create a consumption floor of $\underline{c}$. This feature of the model is taken from Hubbard, Skinner, and Zeldes (1995) and DeNardi, French, and Jones (2010). Based upon the results reported in Cooper and Zhu (2016) this institutional feature is important for matching the wealth income ratio of relatively poor households. Here $B(R^b A^{b'} + R^{s'} A^{s'})$ is the value of leaving a bequest of $R^b A^{b'} + R^{s'} A^{s'}$ and is explained below.

For ease of exposition, this problem is stated with time separable preferences. As reported in Cooper and Zhu (2016), a recursive utility formulation, as in Epstein and Zin (1989) and Weil (1990), fit the moments for the US best. We return to allowing this alternative specification in our estimation section.

The F in (2) represents the cost of stock adjustment account, including fees paid as well as time costs incurred. In Bonaparte, Cooper, and Zhu (2012) and Cooper and Zhu (2016), this cost was used, in part, to match portfolio adjustment rates. Although no data exists on adjustment rates for Chinese asset market participants, the stock adjustment costs motivate a lower stock share for participants which is observable in the data, which enables us to identify F in the SMM estimation.

[12] By value we mean that, for example, A^s, is the product of the amount of stock purchased in the previous period and its realized return.

A household that participates in asset markets but chooses not to adjust its stock account is able to freely adjust its bond account. That is, if the household chooses not to adjust its portfolio, then the cost F is avoided and there is re-optimization over bond holdings alone. The household chooses bonds to maximize:

$$v_t^n(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b} u(c) + \beta E_{y',m'|y,m} \left\{ (1-\nu_{t+1}) v_{t+1}(\Omega') + \nu_{t+1} B(R^b A^{b'} + R^{s'} A^{s'}) \right\}$$

$s.t.$

$$c = y + TR - m + R^b A^b - A^{b\prime} \tag{3}$$

$$A^{s\prime} = R^s A^s \tag{4}$$

$$TR = \max\{0, \underline{c} - (y + \textstyle\sum_{i=b,s} R^i A^i - m)\} \tag{5}$$

where return on stocks is automatically reinvested into the stock account, i.e. $A^{s\prime} = R^s A^s$. By assumption, bond adjustment is costless. Recall that a bond is defined as a composite of the low-return liquid assets (e.g. bank deposit) and housing asset. If the amount of bond adjustment is larger than the holding of low-return liquid assets, then the adjustment involves housing transaction which is clearly not costless. In Section 5, we assess the restrictiveness of this assumption by calculating the bond change rates from the simulated data and compare them to the proportion of liquid asset in composite bond holdings in the 2011 CHFS data.

A household currently participating may choose to end its stock holdings. Though there is no flow cost of participating, household will exit financial markets when a large shock, such as an adverse medical expense, leads to the liquidation of stock holdings. The value of exiting is given by:

$$v_t^x(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b} u(c) + \beta E_{y',m'|y,m} \left\{ (1-\nu_{t+1}) w_{t+1}(\Omega') + \nu_{t+1} B(R^b A^{b'}) \right\} \tag{6}$$

$s.t.$

$$c = y + TR - m + \textstyle\sum_{i=b,s} R^i A^i - A^{b\prime} \tag{7}$$

$$TR = \max\{0, \underline{c} - (y + \textstyle\sum_{i=b,s} R^i A^i - m)\}. \tag{8}$$

3.2 Non-Participant

A household currently not holding stocks can, at a cost, enter into the stock market. Or the household can remain a non-participant. The values for this participation decision are given by:

$$w_t(\Omega) = \max\{w_t^n(\Omega), w_t^p(\Omega)\} \tag{9}$$

for all Ω.

Even if does not hold stocks, the household can adjust its bond account in response to income shocks. The optimization problem of a non-participant who remains a non-participant is:

$$w_t^n(\Omega) = \max_{A^{b'} \geq \underline{A}^b} u(c) + \beta E_{y',m'|y,m} \left\{ (1-\nu_{t+1}) w_{t+1}(\Omega') + \nu_{t+1} B(R^b A^{b'}) \right\} \tag{10}$$

for all Ω. Consumption is given by

$$c = y + TR - m + R^b A^b - A^{b\prime}. \tag{11}$$

If a non-participant switches its status and decides to purchase stocks, it must pay a participation cost of Γ. There is no lag so that the household can instantly trade in the stock market. The value from participating for the first time is given by:

$$w_t^p(\Omega) = \max_{A^{b'} \geq \underline{A}^b, A^{s'} \geq 0} u(c) + \beta E_{y',m'|y,m} \left\{ (1-\nu_{t+1}) v_{t+1}(\Omega') + \nu_{t+1} B(R^b A^{b'} + R^{s'} A^{s'}) \right\}$$

$s.t.$

$$c = y + TR - m + R^b A^b - A^{b\prime} - A^{s\prime} - \Gamma \tag{12}$$

$$TR = \max\{0, \underline{c} - (y + R^b A^b - m)\}. \tag{13}$$

3.3 Functional Forms

The quantitative analysis requires the specification of functional forms, both for the flow utility and the value of bequests. As in Cooper and Zhu (2016), we assume a recursive utility representation following Epstein and Zin (1989) and Weil (1990). The value function is given by:

$$V_t = \left\{ (1-\beta) c_t^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t V_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}. \tag{14}$$

Here γ is the relative risk aversion that captures the attitude of the agent towards risk, and θ is the elasticity of inter-temporal substitution that parameterizes the substitution effects of a change in the real interest rate. With this specification, there two key aspects of household choice are estimated independently.

The bequest function is given by:

$$B(Z) = L \times Z. \tag{15}$$

The curvature over the bequests, parameterized by γ, appears through (14).

4 Quantitative Approach

The parameters of the household optimization problem are estimated via the SMM. The estimates of the income and medical expenses processes, return processes, and mortality, described below, are estimated outside of the household optimization problem.

For the SMM approach, the vector of parameters $\Theta \equiv (\beta_i, \gamma, \theta, L, \Gamma, F, \underline{c})$, solve the following problem:

$$\pounds = min_{\Theta}(M^s(\Theta) - M^d)W(M^s(\Theta) - M^d)' \tag{16}$$

where W, the weighting matrix, is the inverse of the variance-covariance matrix of the moments. Note that the discount factor, β_i, is indexed by educational attainment $i = 1, 2$ where $i = 1$ is the low education group.[13] The simulated moments, $M^s(\Theta)$, are calculated from simulated data set created by solving the household optimization problem.

In the presence of stock market participation costs, the status of being a participant itself has value. Therefore the initial allocation of assets could be important. But this is not a concern in the current study since our estimation is based on two cohorts that enter the economy at around 1970 and 1990 while the stock market became active after 1990. Thus we assume households enter the economy with zero holdings of stocks. By contrast, Cooper and Zhu (2016) calculates the initial distribution of asset holdings from data as initial conditions matter for household choices.

In computing the lifecycle optimization problem, we assume households work for 40 years, between age 21-60. On average the Chinese workers retire at age 60. In contrast, the typical retirement age is 65 in the US. We take the age-dependent mortality rate exogenously from the mortality table in China reported by the National Bureau of Statistics, available at `http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/html/A0604a.htm`. To reduce computational load we assume households die for sure at age 91, although in the data the average probability of death is 19.1%, 21.7% and 45.4% for those aged between 90-94, 95-99 and over 100.

4.1 Regime Change

In working with the Chinese data there is an important challenge: the available data have a time span that is too short to adequately control cohort effects stemming from multiple regimes changes in China. In our CHFS data, households have experienced regime changes at different stages of their lives, which make inference from a single cross section exceptionally difficult. The timing of these structural changes are illustrated in Figure 2.[14]

To appreciate this issue, compare two single men from the sample. One is 35-45 years old with a college education living in Shanghai. This person has a job in the private sector and is a participant in the Shanghai stock market. The other is 60-70 years old. He is now working in the private sector though he began his career working in the public sector. When he was young, there were very few private sector jobs and there was no access to stock markets. Nowadays, nearing retirement, things are very different due to the privatization and other reforms that

[13]In experiments where, in addition to the difference in the discount factor by education, we also allow difference in either the participation cost or the adjustment cost. The estimation results indicate that these additional difference are statistically insignificant.

[14]Another potentially important structural change is the implementation of *the new rural cooperative medical insurance* since 2003 which provide rural households with the basic medical insurance coverage. Since the China Health and Retirement Longitudinal Study (CHARLS), the main source of medical expense data, started only in 2008 on the trail basis, we are not able to measure the impact of this new policy on medical expense process. Data from CHARLS 2011-2013 shows that out-of-pocket medical expense relative to income is still much higher for rural households.

Figure 2: Time line and cohorts

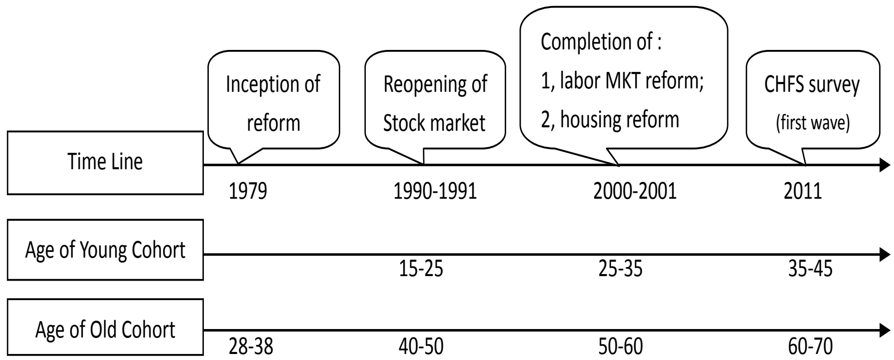
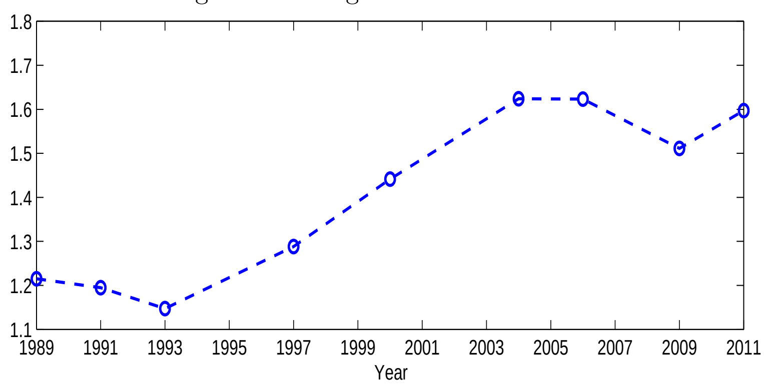


Figure 3: College Premium in China



The figure shows the college premium defined as the multiple of the average labor income of college graduates relative to the average labor income of those without college education. Data source: the China Health and Nutrition Survey.

started in the early 1980s and ended about 20 years later, the re-opening of stock markets around 1990 and and a higher return to education.

Figure 3 shows the college premium over time in China. As a consequence of labor market reform, the college premium rose dramatically from 1989 to 2011. This type of structural change dramatically separates the groups in the single cross section.

The stochastic process of income has also changed dramatically in China. This can be seen in Table 4. The income process for China is estimated from the longitudinal data based on eight waves of China Health and Nutrition Survey between 1989-2009. Comparing the pre- and post-2000 period, one can see that income shocks has been both larger and more persistent. This is especially true for the more educated group. Similar changes about unemployment risk are documented in He, Huang, Liu, and Zhu (2014).

These changes in labor market are related to the rise of private and foreign enterprises, the privatization of collectively owned enterprises, as well as the reform of state-owned enterprises (SOEs). The reform of SOEs, implemented mainly by Premier Rongji Zhu, is particularly impactful. By the beginning of 2000s, the SOEs have mostly been transform into so-called "modern enterprises" that seek profit maximization to a large extent, with the freedom to set wages and unemploy workers.

The participation of stock market was essentially not possible before 1990. Shanghai Stock Exchange started to operate on December 19, 1990. The Shenzhen Stock Exchange also stared to operate on December 1, 1990. Thus for the cohort born in 1950, stock market was simply not accessible until they were 40 years old.[15]

Further, prior to the 2000 housing reform, there was not an active residential housing market. Instead, houses were mostly allocated through the employment relationship rather than through market transactions. After the reform, house prices started to take off, and the average real growth rate of house price in cities has exceed 10% since 2005.[16] Therefore the housing reform is an important structural change which we take into account explicitly in the estimation.

Our approach to estimation is to include the cohort effects from these changes in our model, rather than remove them from the data. Taking access to the stock market as an example, we assume that prior to 1990 various cohorts make financial decisions based on the expectation of no stock market in their lifetime. In 1990 the stock market re-opened and households re-solved their lifetime optimization problem given the new information. That is, the regime switch is a surprise and the new regime is believed to last forever. Clearly the re-optimization is cohort-specific in 1990. For cohorts that entere the labor market in 1990 or later, the re-opening of stock market does not alter their optimal decisions. Based on these optimal decision rules, the simulated data include cohort effects. In the SMM estimation, we take a snapshot of year 2011 from the simulated data to match the the actual data available in the 2011 CHFS.

To implement this, for each education group we solve the dynamic optimization problem for two cohorts who experienced the structural changes at different ages, called the young cohort and the old cohort respectively, as illustrated in Figure 2. For the young cohort, the stock market is always accessible, and the structural change in the labor market occurs ten years after they enter the economy. Their household finance information is represented by those aged 35-45 in the CHFS data. For the old cohort, the stock market is not accessible until they are 45 years of age, and the structural change in labor market occurs when they are 55. Their financial decisions are reflected by household finance moments of those aged 60-70 in the CHFS data.

4.2 Exogenous Processes

As presented in this section, Chinese and US households differ in the exogenous income processes they face over the life-cycle. There are important differences in medical expenses between the two countries. In addition, the asset return processes differ, with a significantly lower Sharpe ratio in China relative to the US.

[15]The security market in Shanghai dates back to the 1860s. It was closed 1950 as part of the socialist transformation.
[16]Most of existing house price indices in China dates back to 2005 or later.

4.2.1 Income

To characterize the stochastic component of income, let $\tilde{y}_{i,t}$ denote the stochastic component of income for household i in period t. We decompose it into transitory and persistent shocks.

$$\begin{aligned} \tilde{y}_{i,t} &= z_{i,t} + \epsilon_{i,t} \\ z_{i,t} &= \rho z_{i,t-1} + \eta_{i,t} \end{aligned} \tag{17}$$

where $\epsilon_{i,t}$ and $\eta_{i,t}$ are independent zero-mean random shocks, with variance σ^2_ϵ and σ^2_η respectively. The shock $\eta_{i,t}$ is persistent, with persistence parameter of ρ.

This stochastic process of labor income is estimated using data from China Health and Nutrition Survey (CHNS) between 1989 and 2011. The estimation procedure is essentially to match the variances and serial correlations of income implied by the above two equations with those calculated from the data, as detailed in Yu and Zhu (2013). The process for the US is estimated from the Panel Study of Income Dynamics (PSID) between 1989 and 2009. More details about the data are in the Appendix. Table 4 reports the estimates for both China and the US.

Table 4: Stochastic Income Processes

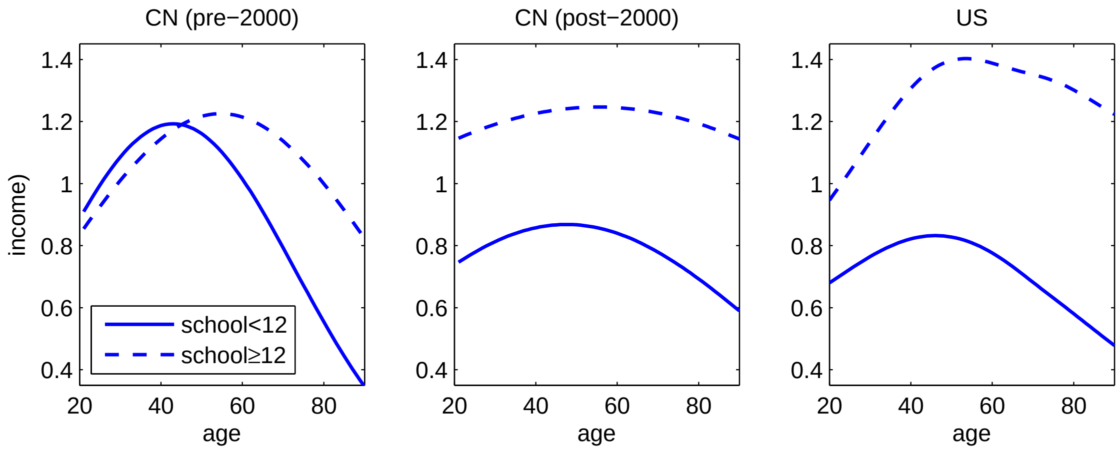
	China pre-2000			China post-2000			US		
Schooling	ρ	σ^2_η	σ^2_ϵ	ρ	σ^2_η	σ^2_ϵ	ρ	σ^2_η	σ^2_ϵ
<12	0.736	0.124	0.382	0.844	0.134	0.329	0.962	0.017	0.108
	(0.022)	(0.023)	(0.034)	(0.011)	(0.015)	(0.031)	(0.008)	(0.003)	(0.022)
≥12	0.708	0.059	0.235	0.832	0.076	0.204	0.955	0.023	0.052
	(0.043)	(0.028)	(0.048)	(0.018)	(0.012)	(0.026)	(0.004)	(0.003)	(0.010)

There are a couple of notable differences. First, the variances of transitory income shocks in China are 3-4 times larger in China than the US, implying much riskier income. Second, income shocks are less persistent in China relative to the US, but the variances of persistent income shocks are 3-9 times larger in China. Overall the persistent component of income shock ($z_{i,t}$) is also more variable in China in terms of the unconditional variance of $z_{i,t}$ which is $\sigma^2_z = \frac{1}{(1-\rho)^2}\sigma^2_\eta$ from equation (17). For the less educated group, values of ρ and σ^2_η in Table 4 imply unconditional variances of 0.68 in China and 0.48 in the US. For the more educated group, the unconditional variances are about the same: 0.50 for China and 0.51 for the US.

The deterministic components of income over the life cycle are shown in Figure 4. To obtain these profiles we have controlled the effects of year, region of residence, gender of househead, and rural-urban status. Income levels are re-scaled so that the average of each education group is one.

For China, the rising education premium is apparent. Estimation based on 1989-2000 data shows a negative education premium before age 45, while the education premium is always positive in post-2000 data. On average income of the high education group is 18% higher than the low education group in pre-2000 data, but the number becomes 54% in post-2000 period. In the US the average income of the more educated group is 78% higher than the less educated in our PSID sample between 1989-2009. Therefore despite the fact that education premium has

Figure 4: Age Profile of Income



The figure shows the average profiles of income by educational attainment. The controls are year, region of residence, gender of househead, and rural-urban status. Income levels are re-scaled so that the average of each education group is one.

risen considerably in China, it is still small compared to the US.

Compared to the pre-2000 income profile, the hump shape is less pronounced in the post-2000 regime. This is especially true for the more educated households, which partly reflects the rising education premium. Compared to the US data, the hump shapes in post-2000 income are also much less pronounced in China. This would, all else the same, lead to less savings in China.

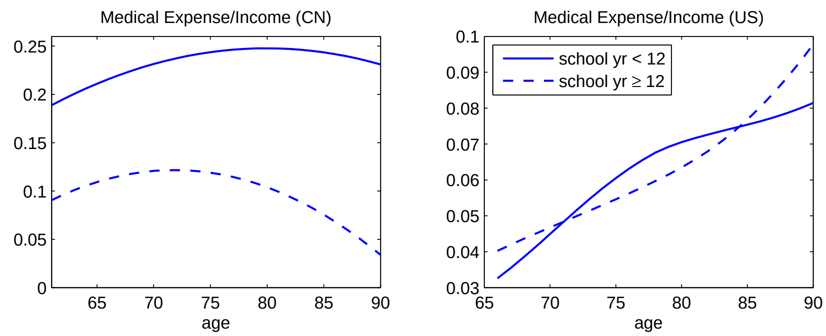
4.2.2 Medical Expenses

Data on out-of-pocket medical expenses are extracted from The China Health and Retirement Longitudinal Study (CHARLS). We use the 2011 and 2013 waves of the survey to estimate the deterministic and stochastic medical expense process. More details about the data and sample selection are provided in the appendix.

For each education group, we calculate the ratio of medical expense to income, then regress the ratio on a quadratic function of age. The left panel of Figure 5 shows the predicted profiles for China. Clearly, relative to their income, less educated households are subject to higher out-of-pocket medical expenses in China, which is in sharp contrast with the US profiles shown in the right panel. This is at least partly due to the fact that the more educated Chinese either enjoy near free health care if they are in the state sector, or they have better medical insurance coverage if they are in the private sector. Compared with the US households, the out-of-pocket medical expense in China has much flatter age profiles, but the average levels are higher, especially for the less educated group. In the counterfactual analysis it will be made clear that the less educated Chinese households would save significantly less if their medical expense profile was the same as their US counterparts.

The stochastic process of out-of-pocket medical expense is estimated with the same procedure used for the income process. Results are presented in Table 5. For comparison, we also show the process for the US as

Figure 5: Post-Retirement Medical Expenditure Relative to Income



The figure shows the average profiles of post-retirement to post-retirement income by educational attainment.

Table 5: Stochastic Medical Expense Process

	China			US		
	ρ	var(η)	var(ϵ)	ρ	var(η)	var(ϵ)
Overall	0.978	0.077	1.875	0.922	0.0503	0.665
	(0.034)	(0.053)	(0.133)			
schooling<12	0.987	0.058	1.904			
	(0.029)	(0.038)	(0.134)			
schooling≥12	0.954	0.107	1.825			
	(0.086)	(0.141)	(0.281)			

estimated in DeNardi, French, and Jones (2006). Apparently Chinese households are subject to larger and more persistent medical expense shocks. The more educated Chinese receive larger shocks, but the shocks tend to be less persistent. However as shown in Figure 5, their deterministic expense relative to income is much smaller, so they are less vulnerable to medical expense shocks overall. In the estimation of the model, these education specific income and medical expense processes are exogenous inputs.

Another exogenous input in the structural model is the age-dependent death probability. For China the death probability is obtain from the mortality table based on the 2010 census. For the US it is estimated from the longitudinal data of the Health and Retirement Survey with the same estimation procedure as in DeNardi, French, and Jones (2010). The cross-country difference is small, which is partly reflected in the life expectancy of 76.1 in China and 79.3 in the US as calculated by the World Health Organization. We use the same death probability for different education group in each country.

4.2.3 Returns on Assets

The asset returns include the returns on stocks, bonds and housing. These processes are inputs into the household optimization problem.

We use the real return to Shanghai Stock Exchange Composite Index, including both dividend and capital gain, for the period between March 1994 - March 2016. The stock return is 10.07% on average, with a standard deviation of 0.47. These statistics are used in the baseline analysis.[17] In the robustness check we also estimate the model based on the (i) stock return prior to March 2011 and (ii) stock return process of the US market explained below.

Risk-free bonds in our model are a composition of housing asset and traditional low-risk assets such as bank deposits, treasury bills and so-called Wealth Management Products (WMPs). We include housing in the composite bond because the housing return has a negligible standard variation compared with the stock return. For example, Fang, Gu, Xiong, and Zhou (2015) reports a standard deviation of housing return of only 0.075 for smaller and median-sized cities between 2003-2013 and a standard deviation of 0.515 for stock return during the same sample period.

Regarding the real return on housing asset in China, the baseline model uses the housing returns of 6.28% reported in Jing Wu and Deng (2012). In the robustness analysis we also consider a return of 11% which is the real return on housing asset in the third-tier cities in China reported in Fang, Gu, Xiong, and Zhou (2015).[18]

Return on risk-free asset is 1.8% based on data on return to 1-year deposit and 90-day treasury bills as reported by People's Bank of China.[19] In our CHFS sample housing asset accounts for 81.5% of the sum of housing asset and the traditional low-risk asset among home owners. This ratio is 81.1% for the low-education group and 80.7% for the high-education groups. Therefore we put a weight of 0.815 on housing and a weight of 0.185 on the traditional low-risk assets to find a return of 5.45% for the composite bond in the baseline model. In the robustness analysis, the composite bond return is set to 9.3% based on a housing return of 11%.

In comparison, in the US the average stock return is 6.33% and the standard deviation is 0.155 based on Robert Shiller's online data of $S\&P500$ for the period 1947-2007. As discussed in Cooper and Zhu (2016), in the US the return on composite bond that includes traditional low-risk asset and housing is 4.08%. Therefore the Sharpe ratio (based on our definition of riskfree asset) is 0.145. For the Chinese counterpart, the Sharpe ratio is 0.091 and 0.021 using the composite bond return of 5.45% and 9.3%, respectively. Therefore the risk-adjusted return is much higher in the US stock market, which partly explains the different household finance patterns between these two countries. As shown in Section 7, in the counterfactual analysis where the US stock return process is imposed in the Chinese model, households have significantly higher stock market participation rate and much higher stock share in total wealth.

In the model households have no access to the stock market prior to the regime change in 1990. Further, since there is no active housing market prior to the regime change in 2000, we set the return on the composite bond to 1.8%, the return on the traditional low-risk assets.

[17] For the period of 2003-2013, Fang, Gu, Xiong, and Zhou (2015) reports the mean and standard deviation of stock return to be 7.3% and 0.515, respectively.

[18] There are 85 third-tier cities in Fang, Gu, Xiong, and Zhou (2015) that are economically and politically important in their respective provinces but are not considered either first-tier (Beijing, Shanghai, Shenzhen and Guangzhou) or second-tier (autonomous municipalities, provincial capitals, or vital industrial/commercial centers). These top three-tier cities have significantly higher returns on housing asset.

[19] `http://www.pbc.gov.cn/zhengcehuobisi/125207/125213/125440/125838/125888/2968985/index.html`.

4.3 Moments

The data moments for China are summarized in the top panel of Table 6. Here the "young cohort" and "old cohort" refer to the 35-45 and 60-70 years old households in the 2011 CHFS respectively. The moments are obtained by regressing the elements of household financial decisions on the dummies of the following four cohort-education pairs: young with low-education, young with high education, old with low-education, and old with high education. The omitted group represents households of any educational attainment in neither the 35-45 or 60-70 cohort. Using the simulated data which also contains cohort effects, we run exactly the same regression to obtain model moments.

In the regressions based on the actual data, homeownership dummy is also included as a regressor. The model does not include a homeownership choice. Yet, homeownership influences financial decisions. For China, we find that homeownership reduces the participation rate and financial wealth (without housing) to income ratio significantly. By controlling for homeownership in the actual data, the data moments are purged of these effects of homeownership, hence are comparable with the model moments. We also included logarithm of housing value as a regressor to obtain the participation moments, which is again meant to purge the participation moments of the housing effects. In the CHFS data, more housing wealth is associated with a higher market participation rate.

The CHFS data also show a positive correlation between housing value and wealth-income ratio. The effects of of housing on stock share are not statistically significant. As already mentioned, our optimization model includes housing wealth in the broadly defined bonds on the basis that the standard deviation of housing return is only about one-seventh of that of the stock return. Accordingly, the stock share moment is defined as the ratio of stock value to the sum of financial and housing wealth. This same measure of wealth is used to calculate the wealth-income ratio. Further, as discussed above, the return to bonds includes the return to housing asset. Thus the role of housing as a component of wealth is captured in this analysis.

The data moments reported in Table 6 capture the same patterns as the averages by age and education reported in Table 1. In particular, participation increases with education while the share varies relatively little. Further the wealth-income ratio is larger for older households and more educated households.

Table 7 summarizes the data moments used in the estimation of the parameters for the US economy. These moments are obtained by regressing household financial choices on age, age-squared, a dummy for higher education, year dummies, and a homeownership dummy.[20] The lifecycle profiles based on the regression coefficients are shown in Figure 1. Again it is clear that participation, stock share and the wealth-income ratio are all increasing in educational attainment. Further, there are significant life cycle patterns in these financial decisions.

5 Estimation Results

This section discusses the estimated parameters and associated moments for both China and the U.S. It then explores the robustness of these estimates. The estimation is also conducted for other sub-groups in China, based on rural-urban status and type of employment.

[20] Cooper and Zhu (2016) reports results for four education groups, both with housing in the moments and conditioning on home ownership status and equity.

5.1 Main Results

Table 8 presents parameter estimates for both China and the US. The comparison across countries is useful for a few reasons. First, the between-country difference in household finance patterns are partly driven by these parameters. Second, the between-country comparison provides a context for evaluating the parameter estimates. The contrast is further enhanced below by looking at estimates for groups within China.

For the Chinese baseline model in the first row, the estimated discount factor of 0.877 for the low education group is considerably lower than the estimate of 0.959 for the high education group. The US parameter estimates are given in the second row of Table 8. For the US the discount factor is also higher for the high education group, though this difference is not statistically significant. Importantly, the discount factors for the Chinese households are much higher than those for the US.

The estimated risk aversion of $\gamma = 7.395$ in China is higher than γ=6.469 in the US, though the difference is not statistically significant. The estimated elasticity of intertemporal substitution in China is $\theta = 0.493$, significantly lower than the $\theta = 0.893$ in the US. For neither country is θ close to $\frac{1}{\gamma}$ as in the CRRA preference specification. The estimated bequest motives for China and the US are fairly close to each other.

The costs of stock market participation are reported as a fraction of average household disposable income in a country. The estimated cost is very high in China, 25.5% of average income, which is needed to match the relatively low participation rate of Chinese households. This is considerably higher than the US estimate of 2.8%. Using average disposable household income of $51,759 for the US and $9,313 in China, the participation cost is estimated at $1,449 in the US and $2,375 in China.[21]

The estimated adjustment cost of 0.051 in China is also significantly higher than a cost of 0.016 in the US. Though we do not have any measure of adjustment frequency in the Chinese data, this cost helps to generate the decline in participation for older agents.

The estimate of consumption floor is 0.79% of the average household disposable income in China and statistically significant. In China, this represents transfers from the government as well as within families and among friends. In the CHFS data, about 5% of the respondents lived in a house that bequeathed or transferred, although the survey does not specify where the transfers are from. The survey also has questions about two types of financial transfers: government transfer which is mainly needs-based and private transfer from parents, relatives, friends and others. These transfers are not regular income, and not included in our income measure. The average government transfer is 1582 yuan and the average private transfer is 4298 yuan.

The estimated consumption floor (as a percentage of average household disposable income) in the US is about 3.3 time larger than China. This, as discussed later, partly explains the lower wealth-income ratio in the US.

The simulated moments for China is reported in Table 6. The model matches the participation moments quite well, capturing both the effects of education and cohort. The dependence of share on both cohort and education is relatively small in the data, and in the model. The model is unable to adequately capture the levels of the

[21] The average household income is calculated our sample of the 2011 CHFS which is 58,021 RMB. This is about 9,313 USD using the exchange rate in the end of 2011. For the US, census data shows that in 2011 the median household income is 50,051 US dollar.

wealth to income ratio though the model does succeed in matching the increase for both older and more educated households.

For the US, Table 7 presents both the data and baseline model moments. From this table, the estimated model captures the effects of cohort and education on the participation, share and wealth-income ratio fairly well. The constants of regressions are less well-fit, partly because the constants are estimated with a large standard errors and the SMM procedure puts less weights on matching them.

5.2 Costly Housing Adjustment

The analysis assumes that there is no cost of adjusting the composite bond, which includes housing. Households frequently adjust their liquid assets on the one hand, due to random shocks to income, medical expense or others. On the other hand households only adjust the holdings of housing asset occasionally. This assumption of costless adjustment could be too restrictive if the model-implied bond adjustment is large and exceeds the household's liquid assets.

We examine the proportion of liquid (non-housing) assets in the total composite bond in the 2011 CHFS data, and compare it with the change rate of bond in the simulated data, defined as $(A^{b\prime} - A^b)/A^b$. Intuitively, if this rate of change is smaller than the proportion of liquid assets in composite bond, then the liquid asset alone is sufficient for the adjustment of total bonds, and the costless bond adjustment assumption is non-restrictive.

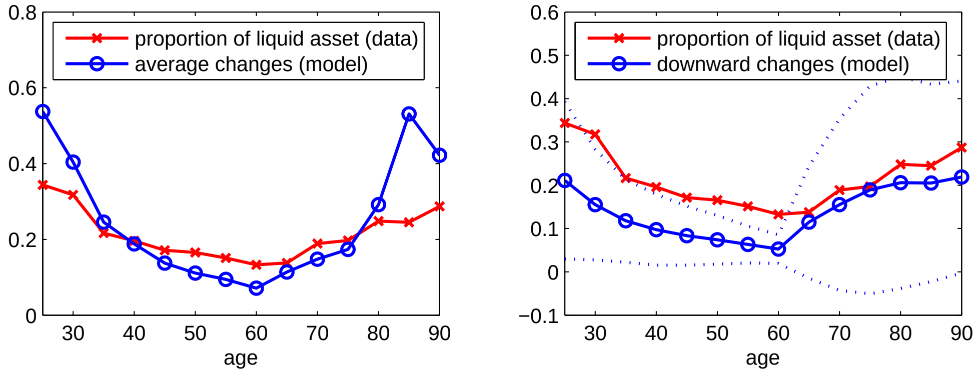
The left panel of Figure 6 shows the proportion of liquid asset in the composite in the 2011 CHFS by age, along with the bond change rate in the simulated data.[22] The bond change rate is well below the proportion of liquid asset for households between ages 45 and 75, but it is well above the proportion of liquid asset before 40 and after 80. Intuitively this is because younger households need to accumulate liquid asset to pay down for housing assets, and old households need to liquidate some housing assets for consumption or medical expenses.

A main concern is whether the liquid proportion in the composite bond is sufficient to buffer against adverse income or medical expense shocks.[23] To answer this question, from simulated data we take incidents in which the bond changes are negative and thus that decrease bond holdings, and re-calculate the rates of change. Results are shown in the right panel: the downward changes are all below the proportion of liquid assets. The right panel also shows the bands of one standard deviation above and below the mean change rates (dotted lines). Before the retirement age of 60, the band is also below the proportion of liquid asset. But after retirement, the band widens considerably and goes beyond the proportion of liquid asset. Therefore, the liquid proportion of the bond is sufficient to buffer against negative income shocks before retirement. In summary, the assumption of costly bond adjustment is not restrictive as far as downward changes of bond due to adverse income and medical expense shocks are concerned.

[22] Since the proportion of liquid asset is calculated from one cross section of data, it is also contaminated by cohort effects.

[23] As shown in Bonaparte, Cooper, and Zhu (2012), a important reason for household to hold bond despite the high equity premium is to use the liquid bond to buffer against income shock and smooth consumption.

Figure 6: Rate of Change in Bond in Simulated Data



The figure shows bond change rate (i.e. $(A^{b\prime} - A^b)/A^b$) in the simulated data. The starred line is the proportion of liquid non-housing asset in total composite bond calculated from the 2011 CHFS. Downward change rate of bond (right panel) is calculated from incidents of bond run-downs as $-(A^{b\prime} - A^b)/A^b$.

5.3 Robustness

This section studies the robustness of our findings for China. We re-estimate a number of perturbations of the baseline model and present the results in Table 6 (moments) and Table 8 (parameters).

Weighting Matrix The first experiment replaces the weighting matrix used in the estimation, the inverse of the variance-covariance matrix, with an identify matrix. Both matrices, in theory, generate consistent estimates of the structural parameters. With this alternative weighting matrix that puts equal weight on each moment, matching the moments associated with the constants and the wealth-income ratio becomes more important.

The main features of the baseline model are retained with this alternative weighting matrix. In particular, the large gap between the discount factors of low and high education households are present, though the differences are slightly less. Further, the stock market participation cost is quite close. However, with the identify matrix, the adjustment cost is higher and not statistically significant. As in the baseline model, the estimated consumption floor and intertemporal elasticity of substitution are both significantly smaller than their US counterparts.

Stock Return Process Given the short history of stock market in China, it is hard to precisely measure the **expected** return and volatility of stock market investment. In the baseline estimation, the stock return is calculated using the realized return based on stocks listed in Shanghai Stock Exchange and Shenzhen Stock Exchange during the period of March 1994 to March 2016. We do two related robustness exercise: (i) assuming US stock return process; (ii) calculating stock return based on the realized return in the period up to 2011, the year of the CHFS survey.

The row labeled “Earlier Stock Return” uses the realized stock return prior to March 2011. In this case, the mean return is 12.57 and the standard deviation is 0.488. For this specification, the estimated values of adjustment cost is slightly higher, which is needed when stock return is higher in order to match the moments related to participation and share. As with the baseline model, the model match the differences between cohorts and education groups fairly well.

The experiment of "US return" replaces the stock return process in China with the US process. This leads to substantially larger participation cost, adjustment cost and coefficient of risk aversion in order to match the Chinese moments. The fit of the model is almost five times worse than the baseline. Evidently, Chinese households are not equating the stock process in China with that in the US in their expectation.

Housing Return The case of "Higher Housing Return" sets the return on housing at 11% annually instead of the baseline value of 6.28% based on Fang, Gu, Xiong, and Zhou (2015). Of course, this increases the return to bonds, which is treated as a composite asset, to 9.3%. In this case, the stocks are less attractive than bonds. To match the participation and share moments, the adjustment costs and coefficient of risk aversion are much lower than the baseline.

CHFS Income There is an interesting difference between the income from the 2011 CHFS and that from the 2011 wave of CHNS. As indicated in Table 9, the mean income levels of the old cohort are only slightly lower than the young cohort in CHNS which is source data for income process estimation. In the CHNS data, income levels of the old cohort are significantly lower than the young cohort. As shown in "young/old" rows, in CHNS data the young cohort has an income level that is 1.034 and 1.18 times larger than the old cohort for the low- and high-education households. The corresponding numbers are 1.225 and 1.638 based on the CHFS data.[24]

The much lower income levels of the old cohort than the young cohort have implications on household finance patterns. As demonstrated in Heaton and Lucas (1997) and Cooper and Zhu (2016), income substitutes bondholdings in household's portfolio choices, and lower income of the old cohort relative to the young cohort implies lower stock share of the old cohort. To see the robustness of our baseline results, we adjust the income profile of each of the four groups (namely the low- and high-education groups in the young and old cohorts), and re-estimate the model parameters.[25] The results are reported in the row labeled "CHFS Income" in Tables 6 and 8. As expected, compared with the baseline results now the old cohort has much lower stock shares. In particular for the more educated groups that have a larger income gap between the young and old cohorts, the stock share is about 5% lower relative to the baseline. The main features of parameter estimation in the baseline, such as the large entry and small consumption floor, and the discount factor heterogeneity, are well preserved.

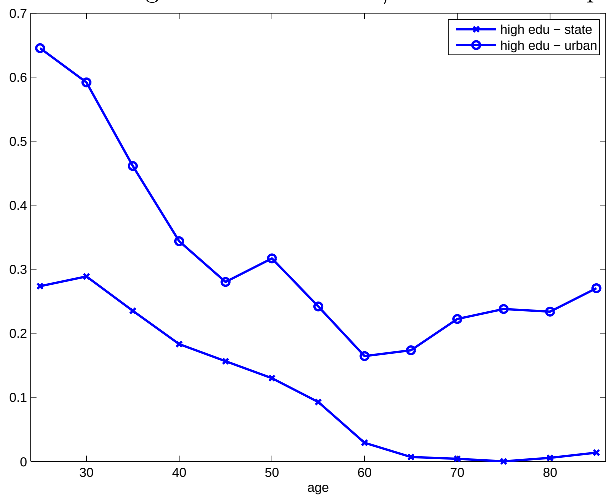
5.4 Other sources of Heterogeneity

As noted earlier, there are are differences in household choices when comparing urban and rural households as well as when comparing public vs. private sector employment. This sub-section re-estimate the model based on these

[24] Since we normalize the average income level to one in the economy, what matters is the relative income of different groups.

[25] To adjust the income profiles, we rotate the baseline income profiles of the young cohort, so that the profiles get steeper until the young and less educated cohort has an income that is 1.225 time larger than the old and less educated cohort, and the young and more educated cohort has an income that is 1.638 time larger than the old and more educated cohort.

Figure 7: Fractions of High-Education Urban/State-Sector Employees by Age



This figure plots the fractions of high-education households that live in the urban area or are employed by the sector sector.

alternative dimensions of heterogeneity.

For these cases, the moments are created by replacing the education-related dummies with those based on either location of residence (rural versus urban) or type of employment, and are reported in Table 10. Comparing to the data moments reported in Table 6 reveals the similarity among the splits based on education, location of residence, and type of employment. This is not surprising given a large fraction of less educated households are rural residents and not employed by the state sector. Nevertheless, compared with the education-based split, the gaps in stock market participation rates and wealth-income ratio are larger in the rural-urban split, and smaller in the employment-based split. In other words, rural residents seems to be in more disadvantageous situation in terms of wealth accumulation and stock market participation.

Parameter estimates are reported in the bottom of Table 8. For the rural-urban split, the estimated discount factor for rural households are significantly smaller than that for urban households, with the difference much larger than in the education-based split. The larger difference is obviously driven by the larger gap in wealth-income ratio. The estimated entry cost is smaller but the adjustment cost is larger. Overall, these parameters do not deviate significantly from the baseline estimates. In particular, the contrast between the Chinese and US parameters are well preserved.

From Table 10, the estimated model matches both the participation and portfolio shares well. The wealth-income ratio is not well matched, partly due to the large standard errors associated with these moments.

Looking at the type of employment, from Table 8, the nonstate-state split generates much smaller estimates for the relative risk aversion and the elasticity of intertemporal substitution. Otherwise, again the parameters are close to the baseline. In fact, the fit of this model is better than the baseline. As for the moments, from Table 10, all the moments related to participation and share are matched very well. But again, the wealth-income ratio moments are not matched well.

As noted earlier, urban residents are more likely to be highly educated. The same is true for the state sector employees. The joint distribution of education type with rural-urban status and with sector of employment is reported in Table 11. To gain understanding of the evolution of joint distributions, we plot the fraction of highly educated urban households and the fraction of highly educated state sector employees against age in Figure 7. These fractions are clearly larger among the young.[26]

6 Regime Change

This section discusses in more detail how the regime changes create a difference in household finance moments of young and old cohorts in our single cross section. In addition, we evaluate to what extent the regime changes matter in terms of the wealth distribution.

6.1 Impact on Household Finance Moments

As noted earlier, a key dimension of the analysis is the introduction of a regime changes into the structural model, which serves two purposes. First, it prevents cohort effects from biasing the SMM estimator by making the simulated data comparable with the 2011 CHFS data. Second, it enables us to quantitatively examine the effects of regime changes through counterfactual experiments, presented in this subsection.

For each experiment, we calculate the averages of household finance moments for the four groups of households in the 2011 cross section of the simulated data: young cohort with high education, young cohort with low education, old cohort with high education, and old cohort with low education. The results are shown in Table 12. For comparison, the first block in the table reports the moments from the baseline model that contains cohort effects from all of the regimes changes shown in Figure 2. This is the benchmark for the experiments.

The first experiment imposes the old income process, including the pre-2000 deterministic and stochastic income for both education groups, throughout the lifetimes of both the young and old cohorts. This results in significantly lower wealth-income ratio for the young cohort, clearly due to the lower degree of income uncertainty in the old income process. The old cohort is in their fifties when the income process switches and are less affected by the change, hence the experiment finds a relatively small difference in the wealth-income ratio compared with the benchmark. In addition, the old deterministic income profile falls more quickly after retirement than the new income profile, especially for the more educated households. This motivates households to save more for retirement. As a result, the more educated old cohort actually have slightly higher wealth-income ratio in the experiment.

In the first experiment, for each of the four groups of households, both the participation rate and stock share are lowered. On the one hand, lower degree of income uncertainty should leads to more risk-taking hence more participation and higher share. But this mechanism is dominated by the lower wealth accumulation which magnifies

[26] The state sector households includes those employed by the governments, the SOEs and the collectively-owned enterprises. In the past 15 years, government jobs have becoming increasing popular among the young. Huawei, the largest telecommunications equipment manufacturer in the world, is classified as a collectively-owned enterprise in China.

the effects of entry and adjustment costs. In addition, the quick decline of income with age in the old regime also causes households to take less risk, hence lower participation rate and stock share.[27]

The second experiment imposes the post-2000 new income process through the lifetimes of both cohorts. Compared with the benchmark, the effects are just the opposite of the first experiment: households accumulate more wealth, participate more, and have higher stock shares in total wealth.

The third and fourth experiments change the housing return. Recall that in the baseline model, the housing return is switched from 1.8% to 6.28% in 2000 unexpectedly as a result of the housing return, leading to a return of 5.45% on the composite bond. For these two experiments, the housing return either stays at the pre-reform level throughout the lifetimes of both cohorts, "Old Housing Return" case, or is at its new level throughout, the "New Housing Return" case.

Keeping the old housing return significantly impacts the moments. Relative to the benchmark, the wealth-income ratio is much lower due to the lower return on housing. The lower return on composite bond leads to a higher Sharpe ratio of stock investment, thus the participation rate and the stock share are both higher for the young cohort. For the old cohort, participation rate and stock share either decrease with remain at about the same level. Hence the low wealth accumulation has a dominatingly negative effect on stock investment despite the higher Sharpe ratio.

The new housing return is much higher than the old. Using the new housing return throughout, each group of households accumulates more wealth. The larger wealth-income ratio diminishes the stock market entry and adjustment costs, which causes more participation and share. The exception is with the highly educated young cohort who have lower participation rate in the experiment. Intuitively, this cohort save less compared with the less educated young cohort due to the relatively flat income profile and lower income risk, hence the wealth accumulation effects are weak for them, and they invest less in the stock market for the high return in the housing market.

In the block labelled "Stock Market always Accessible", we experiment with the case where both old and young cohorts have access to stock market throughout their lifetime, as if the market had always existed. This treatment does not affect the decision of the young cohorts because they enter the economy after stock market re-opens. The less educated old cohort is affected only slightly – with slightly higher participation rate, stock share and wealth-income ratio. The weak effect is partly because the stock market re-opens at a time when the old cohort is about ten years prior to retirement hence they are able to take advantage of the new opportunity in the baseline model to a large extent, and the earlier access does not make a large difference. For the more educated old cohort, the earlier access to stock market increases the participation rate from 20.5% to 28.1%, but wealth-income ratio rises only slightly, implying that participants are less wealthy compared with the benchmark. As a result, stock share (for participants) is lowered by about 1 percentage point.

Table 12 also shows the distances between the counterfactual moments and the baseline moments. For each experiment, four distance measures are reported, pertaining to participation, stock share, wealth-to-income ratio,

[27] Heaton and Lucas (1997) shows that stable labor income largely substitutes out bondholding.

and the overall distance. Specifically the distance is calculated as

$$distance = \sum_{i=1}^{n} \left(\frac{M^i_{baseline} - M^i_{counterfactual}}{\sigma^i_M} \right)^2 \tag{18}$$

where n is total number of moments. For example, the distance pertaining to participation has four moments and the overall distance has twelve moments. $M^i_{baseline}$ is the i^{th} moment from the baseline model and $M^i_{counterfactual}$ is similarly defined, and σ^i_M is the standard error of this moment calculated from the data. Assuming the difference $M^i_{baseline} - M^i_{counterfactual}$ follows a normal distribution, then the distance measure follow a Chi-square distribution with n degrees of freedom. The p-values shows the probability that the distance measure is smaller than the reported distance based on the Chi-square distribution.

A comparison of the p-values reveals that most of the regime changes lead to significant differences as measured by the overall distances, with p-values near one. The only exception is the re-opening of the stock market. Had the stock market always be accessible, stock participation rate would be significantly higher (p-value pertaining to the four participation moments being 0.99), but other moments would have little changes, resulting in a overall distance of 13.25 with p-value=0.65. By examining the distances and p-values pertaining to participation, share and wealth-to-income ratio, it clear that each regime change has a significant impact on participation. But labor market reform has less impact on stock shares. Wealth-to-income ratios are least affected by the regimes changes. They are significantly affected only by the housing market reform: without the reform wealth-to-income ratios would be much lower for each group of households.

In the last experiment, we assume both cohorts have been living in the new regime throughout their lifetimes, with higher income uncertainty, higher education premium, higher housing return, and access to stock market. In this case we see significantly higher participation rate, stock share and wealth-income ratio, particularly for the more educated households. For the new generation in China who have never experienced the regimes changes studied in this paper, this experiment indicates that they should have even higher savings rate and be more involved in the stock market, assuming their preferences are the same as their older generations of course.

The last three columns of Table 12 reports distances between the moments from these experiments and those from the baseline model, weighted by the inverse of the variances of the data moments. These distances measure how much the regime changes affect household financial decisions in China. The p-values indicate the probability that the distance is larger than the reported value, assuming that for each moment the difference between the experiment and the benchmark follows a normal distribution with a zero mean and a variance of the corresponding data moment.

For each of the three dimensions of household finance, i.e. participation, stock share and wealth-income ratio, The second- and third-to last columns report the distances and p-values. The participation moments are greatly affected by each of the regime changes with p-values near ones. Moments related to stock share and wealth-income ratio are less significantly different with small p-values, which mainly reflects the larger variance of these moments. The "New Income Process" and "Old Housing Return" cause the largest changes in participation. Imposing the old and the new housing return throughout causes significant changes to stock share moments, with $p = 0.92$ and $p = 0.99$ respectively. The wealth-income ratio moments is most changed in the "Old Housing Return" experiment with $p = 0.97$.

These results show that regimes changes have significantly shaped household finance patterns in China, and it is important to take them explicitly into analysis when one studies an economy like China.

6.2 Impacts on Wealth Distribution

It is interesting to see how the regime changes impact the wealth distribution in China. Five measures of wealth distribution are considered. The first one is the coefficient of variation of total wealth. This measure mainly captures the overall wealth distribution of households, but it is less informative about the changes of distribution in tails. Therefore three alternatives are used: the mean wealth levels of top 5, 10, 20 percentiles over the corresponding bottom 5, 10 and 20 percentiles. The last one is the probability of hitting consumption floor in the model. A higher probability implies more households with low income and low wealth.

Our goal is to understand to what extent each regime change influences the wealth distribution. Table 13 reports the results. The first row reports moments of the wealth distribution from the data except the probability of hitting the consumption floor which is not available in the data. The distribution from the baseline model, shown in the second row, is much less dispersed than in the data, indicating that the large wealth inequality in China needs to be explained by factors outside our model.

If the income process prior to year 2000 is never changed, then the wealth distribution in the tails is much less dispersed compared with the baseline results. This is shown in the row of "Old Income". Intuitively, college premium is much smaller and income is much less dispersed in the old income regime, with smaller and less persistent shocks. But the coefficient of variation of wealth is slightly larger, indicating some rise in the middle of the income distribution, which is likely to be caused by the less buffered income and medical shocks due to the lower wealth-income ratios.

Conversely, imposing the new income process to years prior to 2000, the wealth distribution becomes more dispersed except that coefficient of variation is lowered slightly, implying fatter tails in the distribution.

With the old housing return imposed to each year in the model, the wealth dispersion increases tremendously compared with the baseline results. About 6% of household live on the consumption floor. Conversely, if the new and higher housing return is applied to each year, then the wealth distribution becomes less dispersed. Mechanically, a higher housing return induces a higher saving rate and attenuates the precautionary motive of saving, hence heterogeneity in income shocks becomes less relevant for wealth accumulation. Notice that we assume every household participates in the housing market. If the housing market is accessible to only a fraction of households, the implication on wealth distribution should be different.

Accessibility to stock market does little change to the wealth distribution, which is consistent with the fact that stock return has an extremely high volatility, but the mean return is not much higher than the composite bond. In other words, the Sharpe ratio is low, so that the stock market participation rate is low, making the accessibility to stock market less important.

In the completely new regime, the overall wealth distribution is less dispersed, but ratio of top 5% (top 10%) to bottom 5% (bottom 10%) is significantly larger, implying that wealth distribution is polarized in the new regime.

Based on a similar model, Cooper and Zhu (2016) studies the probability of hitting the consumption floor in the US. There 26.7% of the less education households hit the floor on average. Even households with college degrees hit the floor with a probability of about 5%. By contrast the Chinese households rely much less on the consumption. Intuitively, this should be attributed to the low consumption floor and the much higher wealth-income ratio in China.

7 China vs the US: Why do they Differ?

This section returns to one of the central questions of this paper: what are the sources of the observed differences in household finance patterns between the US and China? Three sources are potentially important. The first source is preference differences. Estimation results show that Chinese households are significantly more patient and much less willing to substitute inter-temporally. The second source is financial market differences. In our model the underdeveloped financial markets in China relative to the US are reflected in the high entry and adjustment costs, and a highly volatile stock market with lower risk-adjusted returns (lower Sharpe ratios). Third, labor market differ considerably, with a much larger degree of income uncertainty and a underdeveloped social safety net (a lower $\underline{c}$).

An additional source of China-US difference is the regime changes that Chinese households have experienced, as reflected in the cohort effect. We've shown effects of regime changes in Table 12. We will return to this point in the end of this section.

To understand how and to what extent these mechanisms shape the different household finance patterns in China and the US, we conduct four experiments: (i) Chinese households in the US financial market, (ii) Chinese households in the US financial market and labor market, (iii) American households in the Chinese financial market, and (iv) US households in the Chinese financial market and labor market. The American or Chinese households are defined by the country-specific discount factors (β), risk aversion (γ), EIS (θ) and bequest motives (L). A country's financial market is characterized by its bond return, stock return process, and stock market entry cost and adjustment cost. A country's labor market is characterized by its consumption floor, income processes, and medical expense processes.[28]

In the experiment of the Chinese households investing in the US financial market while working in the Chinese labor market, we assume they are subject to the entry and adjustment costs as estimated from the US model, i.e. $\Gamma = 0.028$ and $F = 0.016$. One issue is whether these costs are relative to the average income in the US or in China. If the costs are composed mainly of time cost and search cost for information, then it is reasonable to assume they are relative to the average income in China. Alternatively if they are mainly composed of monetary costs such as commissions of stock trading, then they should be relative to the average income in the US. We assume they are

[28]This paper does not consider cross-country asset allocation which should be an interesting future research topic.

relative to the average income in China on the basis that the literature generally interprets these as information and time costs rather than direct monetary costs.[29]

Results are reported in the top rows of Table 14. On the left side are moments from the four counterfactual experiments and on the right side are the benchmarks. The US benchmark is from the SCF data as in Table 1, while the Chinese benchmark is from simulating the model that controls for cohort effects, i.e. the moments from the "Completely New Regime" in Table 12.

In addition, we also conduct experiments where only one US parameter is imposed on the Chinese at a time, which highlight the relative importance of various parameters. Tables 15 and 16 in the Appendix report results with and without cohort effects respectively.

For the Chinese in the US financial market, the stock market participation rate is almost 100%, except for the less educated young cohort whose participation rate is 70.9%. Wealth-income ratio of the Chinese household is an order of magnitude higher than the US counterparts. Stock share is still lower than the US households, but much higher than the share the Chinese households choose in the Chinese financial market.

If the Chinese households not only invest in the US financial market, but also work in the US labor market, their market participation rate and wealth-income ratio are still significantly higher than the US counterparts, but lower than the Chinese who only invest in the US financial market. On average the stock share is close to the US households, but higher than the Chinese households who invest but not work in the US.

Each of the three mechanisms mentioned earlier in this section is at work here. First, the preference parameters of the Chinese households, in particular the much higher discount factors, lead to their much higher wealth accumulation. The prominent roles played by different discount factors are clearly seen in Tables 16: imposing the US discount factor on China causes the wealth-income ratio in China to fall by 34% to 67% for different groups of households.

Second, in the participation decision the low entry and adjustment costs in the US financial market are almost negligible to the Chinese investor who accumulates massive wealth relative to the US households, which explains the near 100% participation rate. The difference made by the low entry and adjustment costs are also made clear in Tables 16: imposing the US entry cost on China causes the participation rate in China to rise by 60% to 468% for different groups. The higher Sharpe ratio in the US market also contributes to the high participation rate and stock share of the Chinese investors in the US. Tables 16 shows that, by imposing the US stock return process on the Chinese economy, the participation rate and stock share in the Chinese economy are fairly close to those in the US data.

Third, the low labor market risks and high consumption floor in the US leads to less wealth accumulation but more risk-taking, which explains why the Chinese investors in the US have higher wealth-income ratios than the Chinese working and investing in the US, but lower stock share. In the experiment where we impose the US consumption floor in the Chinese economy, the wealth-income ratios are lowered significantly and the average probability of hitting the consumption floor rises from 3.46% to 7.93%. This effect is especially strong for the less

[29] See Bonaparte, Cooper, and Zhu (2012) and Vissing-Jorgensen (2002) for examples.

educated households, which is evident in Tables 15 and 16.

Of course these three mechanisms do not work independently. A important example is the interaction between the lifecycle profile of income in the Chinese labor market and the large difference in the elasticity of intertemporal substitution between the Chinese and Americans ($\theta = 0.493$ for China and $\theta = 0.893$ for the US). Tables 15 and 16 show that when the US value of θ is imposed on the Chinese economy, the less educated Chinese have lower wealth-income ratios yet the more educated Chinese have higher wealth-income ratios. Using the larger US θ, households are more willing to more willing to substitute intertemporally and care less about the rise and fall of consumption over lifecycle, which causes the lifecycle profiles of wealth track those of income more closely. For the more educated, the decline of income occurs later and to a less extent than the less educated households as shown in Figure 4, hence their wealth-income ratio is raised by a larger θ, while the wealth-income ratio of the less educated are lowered by a larger θ.

In the case of US households investing in the Chinese financial market but not working in the Chinese labor market, their stock market participation rate is zero, and on average they accumulate less wealth then Americans in the US financial market. For the Americans who both work and invest in the Chinese market, the market participation is also zero, except that a tiny fraction of the more educated old households (0.1%) will have a tiny share (3.5%) in the stock market in China. But their wealth-income ratio is significantly higher than American who invest but not work in the Chinese markets.

Once again, each of the three sources is at work. First, the low discount factors of the US households lead to much lower wealth accumulation. Second, the high participation and adjustment costs in the Chinese financial market keep the US households, who do not accumulate much wealth, from enter the stock market. Third, the high labor market risks and low consumption floor in the China leads to more wealth accumulation, which explains why the US workers in China have higher wealth-income ratios than the US investors in the Chinese financial market.

As discussed earlier, the regimes changes experienced by the Chinese households also contribute to the cross-country difference in household finance patterns. This point is supported by comparing Tables 15 that includes cohort effects with Table 16 that does not include cohort effects. Both tables present the distances between the Chinese model moments and the US data moments. For most of the experiments, the distance is smaller when cohort effects are excluded. That is, the cohort effects have widened the gap between the US and China in terms of household finance moments.

Finally there is a caveat. We define the low-education group as households with less than or equal to twelve years of education in both countries. By this definition only 12.4% of the population is in the high-education group in China based on the 2010 census data, but corresponding number is 58.9 according to the US census bureau.[30]. If human capital of an individual is a combination of nature and nurture effect, and if the nature effect is drawn from the same distribution both in China and the US, then likely the high-education Chinese have higher human capital levels than their counterparts. However the opposite may arise if the overall quality of college education is sufficiently higher in the US than in China. A interesting extension would be to endogenize education decisions in

[30] https://www.census.gov/content/dam/Census/library/publications/2016/demo/p20-578.pdf.

a household finance model like ours.

Table 6: China: Data and Model Moments

		Young Cohort		Old Cohort	
	const.	low-edu	high-edu	low-edu	high-edu
Data					
part.	0.120	−0.059	0.206	−0.059	0.100
	(0.022)	(0.010)	(0.012)	(0.011)	(0.021)
share	0.124	−0.002	0.009	−0.038	0.048
	(0.023)	(0.023)	(0.014)	(0.026)	(0.025)
W/I	12.478	−1.869	4.444	1.967	5.285
	(2.146)	(1.109)	(1.307)	(1.200)	(2.212)
Model					
China Baseline					
part.	0.118	-0.064	0.204	-0.080	0.088
share	0.094	-0.001	-0.022	-0.029	-0.009
W/I	6.949	0.377	1.600	2.769	4.777
Identity Weight Matrix					
part.	0.098	-0.073	0.083	-0.091	0.134
share	0.096	-0.002	0.008	-0.031	0.004
W/I	7.166	0.029	2.491	1.167	5.894
Earlier Stock Return					
part.	0.114	-0.066	0.202	-0.077	0.070
share	0.097	-0.015	-0.023	-0.016	-0.010
W/I	6.735	-0.035	1.155	2.831	4.919
US Stock Return					
part.	0.095	-0.079	0.086	-0.085	0.071
share	0.231	-0.021	-0.030	-0.036	-0.017
W/I	7.476	1.439	3.004	1.308	4.319
Higher Housing Return					
part.	0.122	-0.064	0.205	-0.072	0.077
share	0.071	-0.022	-0.034	-0.030	-0.041
W/I	5.318	1.170	2.187	2.039	3.496
CHFS Income					
part.	0.103	-0.061	0.185	-0.083	0.103
share	0.089	-0.016	-0.009	-0.045	-0.046
W/I	5.864	0.179	0.573	4.157	4.568

This table reports data moments along with the standard errors, and model moments from various estimations. Housing is included as part of the risk-free assets in data moments.

Table 7: Moments of the US Household Finance

		const.	*age*	age^2	*edu*	
part	**data**	-0.116	0.016	-0.00015	0.267	
	(s.e.)	(0.073)	(0.001)	(0.00001)	(0.010)	
	model	-0.312	0.015	-0.00016	0.274	
share	**data**	-0.113	0.013	-0.0001	0.115	
	(s.e.)	(0.074)	(0.001)	(0.00001)	(0.015)	
	model	0.044	0.011	-0.0001	0.118	
		const.	*age*	age^2	$age \times edu$	$age^2 \times edu$
W/I	**data**	1.733	-0.045	0.00088	-0.01	0.00038
	(s.e.)	(0.407)	(0.008)	(0.00008)	(0.004)	(0.00007)
	model	0.379	-0.045	0.00094	0.002	0.00027

This table reports US household finance moments (regression coefficients with housing value and home ownership status controlle) from the data and the model. "edu" stands for the dummy for households with more than high school education. For the wealth-income ratio, this education dummy is interacted with age and the age-squared.

Table 8: Parameter Estimates

	β_1	β_2	Γ	F	γ	θ	$\underline{c}$	L	Fit
China (Baseline)	0.877	0.959	0.255	0.051	7.395	0.493	0.079	1.877	32.46
	(0.017)	(0.004)	(0.040)	(0.009)	(0.654)	(0.019)	(0.032)	(0.459)	
US Economy	0.824	0.842	0.028	0.016	6.469	0.893	0.264	1.960	43.98
	(0.007)	(0.004)	(0.008)	(0.003)	(0.241)	(0.058)	(0.063)	(0.563)	
China (Robustness)									
Identity Weight Matrix	0.871	0.968	0.261	0.091	8.54	0.526	0.102	2.564	3.38
	(0.043)	(0.018)	(0.427)	(0.390)	(1.768)	(0.305)	(0.051)	(0.890)	
Earlier Stock Return	0.867	0.94	0.275	0.083	7.986	0.563	0.076	1.301	35.49
	(0.008)	(0.008)	(0.109)	(0.034)	(1.168)	(0.146)	(0.055)	(0.775)	
US Stock Return	0.874	0.975	0.387	0.272	12.412	0.426	0.081	3.488	159.21
	(0.006)	(0.004)	(0.052)	(0.017)	(0.004)	(0.019)	(0.025)	(0.387)	
Higher Housing Return	0.834	0.946	0.264	0.012	6.495	0.367	0.139	2.479	53.88
	(0.017)	(0.015)	(0.068)	(0.005)	(1.644)	(0.075)	(0.052)	(0.869)	
CHFS Income	0.907	0.954	0.234	0.029	4.727	0.542	0.088	3.753	51.75
	(0.004)	(0.007)	(0.045)	(0.004)	(1.223)	(0.037)	(0.016)	(0.428)	
Rural-Urban	0.838	0.961	0.192	0.076	7.315	0.573	0.084	1.722	70.06
	(0.033)	(0.009)	(0.117)	(0.046)	(2.653)	(0.148)	(0.032)	(0.079)	
Nonstate-State	0.854	0.962	0.300	0.041	5.827	0.351	0.074	1.337	37.51
	(0.009)	(0.032)	(0.177)	(0.005)	(0.842)	(0.023)	(0.054)	(0.663)	

This table reports parameter values from various estimations. The "US return" estimation imposes US stock return to the Chinese market. The "US Economy" represents the estimation based on the US household finance moments and the US exogenous processes. For the first four cases, β_i for $i = 1, 2$ refers to education groups. For the "Rural-urban", β_1 refers to rural households. For the "Nonstate-state" case, β_1 refers to households with jobs in the non-state sector.

Table 9: Mean Households Income in 2011

	Young Cohort		Old Cohort	
	low-edu	high-edu	low-edu	high-edu
CHNS (baseline)	39318	73583	38022	62377
(s.e.)	(2194)	(3435)	(1440)	(3291)
young/old	1.034	1.180		
CHFS (robustness)	43110	115880	35180	70750
(s.e.)	(2847)	(10682)	(2823)	(11854)
young/old	1.225	1.638		

This table reports the mean values of income and their standard errors for the young and old cohorts from two different data sources.

Table 10: China: Moments by Rural-Urban Status and Sector of Employment

		Young Cohort		Old Cohort	
	const.	rural	urban	rural	urban
Data					
part.	0.117	−0.081	0.224	−0.085	0.134
	(0.024)	(0.014)	(0.013)	(0.015)	(0.022)
share	0.121	−0.016	0.016	0.009	0.052
	(0.023)	(0.047)	(0.013)	(0.067)	(0.025)
W/I	13.368	−6.792	4.161	−3.653	6.030
	(2.286)	(1.439)	(1.359)	(1.559)	(2.334)
Model					
part.	0.107	-0.106	0.217	-0.106	0.116
share	0.104	-0.019	-0.039	-0.058	-0.009
W/I	5.543	-0.766	1.589	0.266	6.062
		Young Cohort		Old Cohort	
	const.	non-state	state	non-state	state
Data					
part.	0.117	−0.015	0.247	−0.028	0.038
	(0.058)	(0.010)	(0.016)	(0.011)	(0.058)
share	0.121	−0.001	0.014	0.008	−0.014
	(0.079)	(0.016)	(0.016)	(0.019)	(0.079)
W/I	12.312	1.203	−1.151	2.602	3.755
	(6.052)	(1.016)	(1.642)	(1.113)	(6.076)
Model					
part.	0.134	-0.017	0.245	-0.029	0.042
share	0.117	-0.029	-0.056	-0.030	-0.018
W/I	6.981	-0.957	2.472	2.471	6.188

This table reports model moments from various estimations. Housing is included as part of the risk-free assets in data moments.

Table 11: Joint Distribution of Households

	Low-edu	High-edu		Low-edu	High-edu
Rural	2312	389	Non-state	4311	1714
Urban	2229	2214	State	230	889

This table reports the joint distribution of households by education, rural-urban status and sector of employment.

Table 12: Counterfactual Experiments on Regime Changes

	Young Cohort		Old Cohort		Distance	p-value	Distance
	low-edu	high-edu	low-edu	high-edu	(w.r.t. CN baseline)		(total)
Baseline Model							
part	0.054	0.321	0.037	0.205			
share	0.093	0.071	0.065	0.085			
W/I	7.326	8.549	9.718	11.723			
Old Income Process							
part	0.048	0.254	0.031	0.116	50.2	1.00	58.77
share	0.090	0.044	0.049	0.077	4.42	0.65	(p=1)
W/I	5.647	6.793	9.703	12.124	4.12	0.61	
New Income Process							
part	0.084	0.691	0.051	0.394	1041	1.00	1047
share	0.089	0.082	0.073	0.105	1.32	0.14	(p=1)
W/I	7.459	11.003	9.085	13.689	4.60	0.67	
Old Housing Return							
part	0.066	0.686	0.024	0.152	935	1.00	954
share	0.096	0.110	0.067	0.067	8.22	0.92	(p=1)
W/I	5.518	7.210	6.886	8.912	10.8	0.97	
New Housing Return							
part	0.054	0.144	0.055	0.321	251	1.00	266
share	0.100	0.121	0.072	0.096	12.9	0.99	(p=1)
W/I	7.752	9.005	11.006	13.147	1.82	0.23	
Stock Market Always Accessible							
part	0.054	0.321	0.039	0.281	13.09	0.99	13.23
share	0.093	0.071	0.066	0.076	0.12	0.002	(p=0.65)
W/I	7.326	8.549	9.759	12.009	0.02	0.00	
Completely New Regime							
part	0.088	0.329	0.071	0.507	228	1.00	258.89
share	0.097	0.135	0.080	0.121	23.3	1.00	(p=1)
W/I	7.961	11.425	10.413	15.067	7.77	0.90	

This table presents results from counterfactual exercises to determine the quantitative effects of regime changes in China on household financial decisions. The distance is measured by the sum of squared differences between the counterfactual moments and the moments from the benchmark model, weighted by the inverse of the variances of data moments. The "p-value" column shows the probability of the distance being smaller than the reported distance. The last column shows the total distance between moments from the baseline model and the counterfactual.

Table 13: Wealth Distribution

	c.v. of wealth	top 5% / *bottom*5%	top 10% / *bottom*10%	top 20% / *bottom*20%	prob. (%) of hitting $\underline{c}$
data	*2.00*	*4117*	*974*	*176*	*n.a.*
baseline	**0.91**	**1166**	**326**	**43.73**	**3.63**
Old Income Process	1.03	682	251	35.06	3.01
New Income Process	0.88	2016	448	40.43	3.69
Old Housing Return	1.20	2729	569	100.3	5.90
New Housing Return	1.06	1062	287	36.18	3.40
Stock Market Always Accessible	0.93	1168	326	43.81	3.62
Completely New Regime	0.80	1775	394	33.88	3.46

This table reports statistics for the wealth distribution from the data, the baseline model and the experiments with regimes changes.

Table 14: Cross-country Counterfactuals

	Counterfactual				**Benchmark**			
	Young Cohort		Old Cohort		Young Cohort		Old Cohort	
	low-edu	high-edu	low-edu	high-edu	low-edu	high-edu	low-edu	high-edu
	Chinese in the US Market				US (data)			
	financial market							
part	0.913	1.000	0.709	0.995	0.174	0.550	0.209	0.646
share	0.253	0.267	0.172	0.192	0.258	0.379	0.232	0.364
W/I	7.629	12.047	10.036	16.175	0.313	1.260	3.867	6.454
	financial market + labor market							
part	0.446	0.940	0.268	0.941				
share	0.411	0.358	0.199	0.203				
W/I	1.456	6.239	2.593	10.429				
	American in the CN Market				CN (w/o cohort effect)			
	financial market							
part	0	0	0	0	0.088	0.329	0.071	0.507
share	0	0	0	0	0.097	0.135	0.080	0.121
W/I	0.493	0.776	0.483	1.652	7.961	11.425	10.413	15.067
	financial market + labor market							
part	0	0	0	0.001				
share	0	0	0	0.035				
W/I	3.333	2.418	3.278	4.276				

This table report four counterfactuals (the left panels) and the benchmarks (the right panels). "Chinese" are defined as households with the preference parameters estimated from the Chinese model, including discount factors (β's, risk aversion (γ), EIS (θ), and bequest motive (L). "American" are similarly defined. The financial market of a country is characterized by its stock market entry cost (Γ), stock adjustment cost (F), return on bond, and the stochastic process of stock return. The labor market of a country is characterized by its consumption floor ($\underline{c}$), income processes and medical expense processes.

8 Conclusions

This paper studied household financial decisions for different education and age groups in China, and compare them with those in the US. Patterns of household finance, including participation in asset markets, portfolio shares, stock adjustment rates and wealth to income ratios are studied jointly by estimating and simulating a lifecycle optimization model. This broadens the analysis beyond the dimension of the high savings rates in China.

One key point of the analysis is to uncover to what extent the major regimes changes in the labor market and financial market in China have impacted household finance patterns observed in the data. Counterfactual experiments reveals that the higher income uncertainty due to labor market reform has significantly increases wealth accumulation of households, which in turn raised stock market participation rate and the share of stock in total wealth. The high return to housing investment after the housing return has also boosted wealth accumulation, but it lowered stock market participation for the young households. The inaccessibility of stock market prior to 1990 has relatively less impact on household finance patterns observed in the 2011 data.

Another important point of the analysis is to uncover the key determinants of the different household finance patterns between China and the US. We find significant differences in driving forces. Households in China (i) have different preferences with more patience and more willingness to substitute their consumption inter-temporally; (ii) face different financial market with higher equity market entry and adjustment costs; (iii) face different labor market with more variable income and underdeveloped social safety net. Each of these driving forces plays a quantitatively important role. In the counterfactual experiment where Chinese households work in China but invest in the US market, we find their wealth-to-income ratios are even higher than observed in the Chinese data, and their average stock market participation rate exceeds 80%. If these Chinese households work in the US (hence are exposed to less income risks and protected by a higher consumption floor), their wealth-income ratio would fall due to less precautionary motives, but stock share in total wealth would rise, reflecting more risk-taking due to less labor market risks.

As it stands, the study excludes a couple of other key factors influencing savings and housing demand. One, emphasized in Wei and Zhang (2011), invokes the importance of housing in attracting a spouse. The second is significance of family size in determining savings, particularly with a binding constraint on family size, as in Choukhmane, Coeurdacier, and Jin (2013). Both of these influences on savings and portfolios deserve further attention.

Appendices

A Data Appendix

The key data set for this study is the China Household Financial Survey. Information on the data is available athttp://www.chfsdata.org/.[31] The moments used for the estimation were computed from these data.

A.1 China: Exogenous Processes

Returns Stock return is calculated based on Shanghai Stock Exchange Composite Index, available from W/IND data base (http://www.wind.com.cn/en/Default.aspx). The real return includes dividends and capital gains weighted by their market values, controlled for inflation using CPI. First we calculate the real returns based on quarterly data, then compounded them into annual data. Using the period of March 1994 - March 2016, the annualized mean return is 10.07% on average with a standard deviation of 0.47. These statistics are used in the baseline model. For robustness, real stock return between March 1994 - March 2011 is also calculated. The resulting annualized mean return is 12.57% with a standard deviation of 0.488. The mean return is higher than from the longer sample period, partly reflecting the stock market crash since June 2015. Since the CHFS survey is done in 2011, we also estimated the model based on the shorter sample. As a cross check, we also calculated the value weighted average return of all the stocks listed in Shanghai Stock Exchange and Shenzhen Stock Exchange during the period of 1994-2013, from GTA data base (http://us.gtarsc.com/). The annualized real return is 12.43% with a standard deviation of 0.492. These are extremely close to the returns based on Shanghai Stock Exchange Composite Index. Compared with the US data, both the return and volatility are significantly higher. Consistent with findings in the US market, we cannot reject the hypothesis that stock return follows an i.i.d. process in China.

A prominent trait in China household finance is the dominance of housing asset in the portfolio. Among the three major categories of asset (bond, stock, housing equity), the share of housing asset is 80% on average based on the 2011 CHFS. Excluding stock, housing asset accounts for 88.1% of the sum of housing asset and the traditional low-risk asset among home owners. This ratio is 87.6% for the low-education group and 88.9% for the high-education groups. Therefore The housing market started to be marketized since the end of 1990s. House price then started to take of after 2000, leading to a high average rate of growth. On the other hand, the standard deviation of housing return is only 0.075 for smaller and median-sized cities according to Fang, Gu, Xiong, and Zhou (2015). Thus we categorize housing as a low-risk asset, and combine it with other traditional low-risk assets, including cash, current deposits (checking account), fixed deposits (CDs), WMPs, treasury bills, corporate bonds, investment trust, nonRMB asset, and cash lent to friends and relatives. Collectively these assets are named bond in this paper.

Consistent with our definition of bond, bond return should be the weighted average of housing return and

[31] The China Household Finance Survey (CHFS) is provided by the Survey and Research Center of China Household Finance, Southwestern University of Finance and Economics, Chengdu, China. For more detail about the dataset, please see Gan, Yin, Jia, Xu, Ma, and Zheng (2013).

return to traditional low-rick assets. The average annual return to bank deposits are available on the website of People's Bank of China (`http://www.pbc.gov.cn/zhengcehuobisi/125207/125213/125440/125838/125888/index.html`). Between 1990-2014, after inflation adjustment using CPI, one-year bank deposit has an average annual return of 1.87%. During the same period of time, 90-day treasury-bill in China has an real annual return of 1.75%.[32]. We include in the traditional low-risk assets the so-called wealth management products (WMPs). These are mutual funds issued by state-owned commercial banks. They are typically considered low-risk products. About 26% of them have returns guaranteed explicitly by the issuing bank. The remaining do not have guaranteed returns, but banks tend to choose to repay investors even if the products fail to meet the expected performance set forth by the banks. On average the real return of WMPs is between 2-4%. The WMPs require a minimum level of fund so the access is limited.[33]. In the quantitative analysis we take return on these low-risk non-housing asset to be 1.8%.

There are various estimates of the average housing return. This is mainly due to the discrepancies among the house price indices complied by different institutions. Jing Wu and Deng (2012) shows that nationwide real house has grown 240% between the first quarters of 2000 and 2010, amounting to an annual growth rate of about 3.42%. Jing Wu and Deng (2012) also shows that price-to-rent ratio has a mean value of about 35 implying a rental return of 2.86%. Therefore the overall housing return is 3.42%+2.86%=6.28%. We combine this with the return of traditional low-risk assets and calculate the return on the composite bond. Based on the share of housing asset, we put a weight of 0.881 on housing and a weight of 0.119 on the traditional low-risk assets, thus the composite bond return is set at 5.75% in the baseline model.

An alternative sources of housing return is Fang, Gu, Xiong, and Zhou (2015) which reports that, between 2003-2013, annual housing returns are 15.7%, 13.5% and 11% respectively among the first-, second- and third-tier cities in China. We take the housing return of 11% from the third-tier cities and combine it with the return on traditional low-risk assets, reaching a return of 9.0%.

Income Data Income processes in this paper are estimated based on nine waves of China Health and Nutrition Survey (CHNS). CHNS is an ongoing international collaborative project between the Carolina Population Center at the University of North Carolina at Chapel Hill and the Chinese Center for Disease Control and Prevention. The CHNS conducts surveys regions that vary substantially in terms of geography, economic development, public resources, and health indicators over a 3-day period using a multistage, random cluster process to draw a sample of about 4400 households with a total of 26000 individuals for each wave. The first wave of survey was conducted in 1989, followed by 1991, 1993, 1997, 2000, 2004, 2006, 2009 and 2011 waves during which surveyed households were revisited.

CHNS provides detailed income information as well as a rich set of demographic variables of household members, including age, marital status, education attainment, occupation and industry of employment. We use these demographic variables to filter out predictable component of income. The survey consistently constructs nine

[32]Data available at `https://research.stlouisfed.org/fred2`.

[33]Perry and Weltewitz (2015) provides a nice description of WMPs in China.

categories of income for each household in each wave of survey – business, farming, fishing, gardening, livestock, non-retirement wages, retirement income, subsidies, and other income. Detailed information about these household income categories are available at `http://www.cpc.unc.edu/projects/china/data/datasets/Household%20Income%20Variable%20Construction.pdf`. We estimate household income processes based on the income measured as the sum of the nine income categories.

We select households that have valid information on income, rural-urban status, region, as well as the following information for household heads: age, gender, education attainment, occupation and sector of employment. The following households are excluded: (i) households with zero income; (ii) households whose income grow by more than 2000% between any two surveys; (iii) households whose income drop by more than 2000% between any two surveys.

Medical Expense Data For medical expense deterministic profiles and stochastic processes, we use the 2011 and 2013 waves of the China Health and Retirement Longitudinal Study (CHARLS), available at `charls.pku.edu.cn/`. CHARLS is a longitudinal survey being conducted by the National School of Development at Peking University

The pilot survey was conducted in two provinces (Zhejiang and Gansu) in 2008 and collected data on about 1600 households. Since 2011 the survey collects a representative sample of Chinese 45 and older every two years. The survey data contain information on household demographics, health status, health care expenses, health insurance coverages, employment, income, consumption and assets. Similar to French and Jones (2004) which uses the Health and Retirement Study (HRS) data, total out-of-pocket medical expense is the sum of insurance premium, outpatient expense, hospitalization expense and self-treatment expense. Since CHARLS is designed on the models of HRS, These two data sources are highly comparable and so are the definitions of out-of-pocket medical expenses in China and the US.

We select survey respondents that provide valid information in both waves regarding the following variables: out-of-pocket insurance premium (variable EA006), total outpatient expense (variable ED006), self-paid outpatient expense (variable ED007), transportation cost to medical facilities (variables ED015 and EE015), total treatment and medication cost (variable ED023), self-paid treatment and medication cost (variable ED024), total hospitalization cost (variable EE005) and the self-paid part (variable EE006), total self-treatment cost (variable EF002) and the self-paid part (variable EF003), total cost of dental care (variable EH003) and the self-paid part (variable EH004). We also drop respondents who do not provide valid information on age, education attainment, gender, hukou (rural versus urban), and sector of employment.

A.2 US: Exogenous Processes

The US income processes and medical expense processes are estimated based on the Panel of Income Dynamics (1989-2009) and the Heath and Retirement Study (waves of 1996, 1998, 2000, 2002, 2004, 2006 and 2008). Details on these processes as well as stock return, bond return and housing return are provided in Cooper and Zhu (2016).

B Counterfactuals Using US Parameters

Tables 15 further shows why household finance patterns differ between China and the US by imposing US parameters or processes on the Chinese model once at a time. For each experiment, the distance of its moments from the Chinese benchmark model is calculated using equation (18) and the p-values are the probability that the distance as per its distribution is smaller than the calculated distance. Replacing $M^i_{baseline}$ in equation (18) with the data moments in the US based on the SCF data, we also report the distance relative to the US data and the associated p-value in the last columns of the tables.

As is evident in the table, imposing the US discount factor, EIS and stock market entry and adjustment costs brings a largest changes to the household finance moments in China. The last column of the table shows that when the US stock adjustment cost is imposed on China, the distance between the Chinese model moments and the US data moments is 1153, which is the smallest among all the distance reported in the last column. When the US stock return is imposed on China, the distance of 1413 is also relatively small. In other words, with US stock return or US stock adjustment cost, the Chinese household financial decisions are relative to the US data.

Table 16 removes the cohort effects resulting from the multiple regimes change and repeat all the experiments reported in Table 15. Here the benchmark is the case of "Completely New Regime" in Table 12. Comparing the last column in this table with that in Table 15, we find that the distances to the US data moments in the absence of cohort are mostly smaller, indicating that cohort effects are partly responsible for the large difference in household finance patterns between China and the US. In particularly, when the US stock return is imposed on China, the distance between the model moments in China and the data moment in the US is only 767. The participation rate and stock share in total wealth of the more educated Chinese households are fairly close to their US counterparts.

Table 15: US parameters for Chinese Households (With Cohort Effect)

		Young Cohort		Old Cohort		Distance	p-value	*Total distance*	Distance	*Total distance*
		low-edu	high-edu	low-edu	high-edu	(CN benchmark)			(US data)	
Benchmark	part	0.054	0.321	0.037	0.205				1191	1991
(China)	share	0.093	0.071	0.065	0.085				700	
	W/I	7.326	8.549	9.718	11.723				100	
US Parameter										
β	part	0.006	0.0001	0.006	0.002	842	1.00	890	3667	4392
	share	0.095	0.090	0.060	0.029	6.91	0.86		699	
	W/I	5.042	3.273	6.146	4.217	40.7	1.00		25	
γ	part	0.056	0.398	0.038	0.205	40.9	1.00	41	981	1773
	share	0.087	0.069	0.074	0.088	0.22	0.01		703	
	W/I	6.901	8.247	9.260	11.476	0.36	0.01		89	
θ	part	0.018	0.771	0.009	0.835	2320	1.00	2339	993	1757
	share	0.099	0.072	0.064	0.146	6.17	0.81		646	
	W/I	5.970	10.703	8.443	17.709	12.62	0.99		118	
L	part	0.052	0.313	0.034	0.197	0.75	0.06	0.8	1248	2048
	share	0.094	0.072	0.065	0.082	0.01	0.00		701	
	W/I	7.348	8.522	9.578	11.584	0.02	0.00		99	
Γ	part	0.453	0.764	0.089	0.458	3125	1.00	3132	1298	2182
	share	0.042	0.064	0.088	0.057	7.13	0.87		777	
	W/I	7.556	8.847	9.943	12.067	0.15	0.003		108	
F	part	0.134	0.679	0.102	0.496	1178	1.00	1181	275	1153
	share	0.064	0.065	0.046	0.057	3.51	0.52		775	
	W/I	7.380	8.715	9.770	11.897	0.03	0.00		103	
$\underline{c}$	part	0.043	0.300	0.014	0.166	12.24	0.99	22	1441	2199
	share	0.090	0.071	0.084	0.083	0.56	0.03		695	
	W/I	6.114	8.220	6.282	10.952	9.49	0.95		64	
Return	part	0.056	0.264	0.083	0.410	136	1.00	231	964	1413
(stock)	share	0.185	0.156	0.218	0.153	94.8	1.00		334	
	W/I	7.526	8.957	10.423	13.023	0.82	0.06		115	
Return	part	0.066	0.463	0.028	0.176	144	1.00	146	941	1723
(bond)	share	0.086	0.075	0.080	0.071	0.81	0.06		699	
	W/I	6.827	8.209	8.829	10.517	1.11	0.11		83	
Income	part	0.007	0.304	0.003	0.246	38	1.00	41	1413	2267
(determinist.)	share	0.089	0.056	0.041	0.088	2.20	0.30		763	
	W/I	6.910	8.380	8.830	12.834	0.95	0.08		90	
Income	part	0.000	0.307	0.001	0.219	42	1.00	94	1482	2144
(stochastic)	share	0.032	0.094	0.040	0.151	17.49	0.998		638	
	W/I	2.452	6.427	5.596	9.674	34.38	1.00		23	
Medical Exp	part	0.049	0.310	0.008	0.158	13	0.99	17	1432	2231
(determinist.)	share	0.094	0.071	0.044	0.081	0.69	0.05		715	
	W/I	7.293	8.392	7.785	11.025	2.68	0.39		84	
Medical Exp	part	0.049	0.301	0.008	0.100	35	1.00	41	1594	2414
(stochastic)	share	0.094	0.070	0.040	0.061	1.87	0.24		741	
	W/I	7.292	8.149	7.563	9.661	4.15	0.61		79	

This table reports counterfactuals from imposing US parameters (one parameter at a time) on the Chinese households. The distance is measured by the sum of squared differences between the counterfactual moments and the moments from the benchmark model using the inverse of the variances of data moments as weights. Both the distance relative to the baseline model moments and the distance relative to US data moments are presented. The "p-value" column shows the probability of the distance being smaller than the reported distance (relative to the baseline model). The columns labeled "Total" reports the sum of distances in participation, stock share and W/I.

Table 16: US parameters for Chinese Households (Without Cohort Effect)

		Young Cohort		Old Cohort		Distance	p-value	*Total distance*	Distance	*Total distance*
		low-edu	high-edu	low-edu	high-edu	(CN benchmark)			(US data)	
Benchmark	part	0.088	0.329	0.071	0.507	0.00	0.00		614	1247
(China)	share	0.097	0.135	0.080	0.121	0.00	0.00		481	
	W/I	7.961	11.425	10.413	15.067	0.00	0.00		152	
US Parameter										
β	part	0.011	0.001	0.020	0.006	1399	1.00	1501	3585	4357
	share	0.083	0.077	0.060	0.032	31.06	1.00		744	
	W/I	5.269	3.749	6.438	5.091	71.43	1.00		28	
γ	part	0.072	0.317	0.070	0.505	3.68	0.55	4.5	686	1290
	share	0.108	0.136	0.090	0.125	0.40	0.02		465	
	W/I	7.469	11.121	9.968	14.923	0.39	0.02		138	
θ	part	0.035	0.527	0.032	0.932	721	1.00	741	641	1238
	share	0.090	0.146	0.073	0.195	9.55	0.95		413	
	W/I	6.565	13.860	9.742	19.750	9.82	0.96		184	
L	part	0.086	0.326	0.066	0.496	0.57	0.03	0.6	645	1278
	share	0.097	0.135	0.080	0.118	0.01	0.00		482	
	W/I	7.954	11.399	10.287	14.904	0.02	0.00		150	
Γ	part	0.412	0.820	0.113	0.626	2775	1.00	2792	1152	1971
	share	0.049	0.087	0.083	0.104	16.93	0.998		660	
	W/I	8.090	11.772	10.537	15.202	0.10	0.001		160	
F	part	0.110	0.355	0.168	0.870	387	1.00	391	433	1137
	share	0.087	0.128	0.049	0.086	3.78	0.56		550	
	W/I	7.976	11.458	10.489	15.184	0.008	0.00		154	
$\underline{c}$	part	0.071	0.319	0.036	0.473	16.33	0.997	25	793	1380
	share	0.098	0.136	0.097	0.119	0.41	0.020		473	
	W/I	6.830	11.238	7.291	14.715	7.78	0.90		115	
Return	part	0.085	0.354	0.114	0.736	138.31	1.00	247	438	767
(stock)	share	0.196	0.228	0.198	0.241	106.22	1.00		149	
	W/I	8.054	12.094	10.964	18.040	2.28	0.32		179	
Return	part	0.094	0.338	0.051	0.481	5.75	0.780	12	645	1326
(bond)	share	0.093	0.114	0.088	0.091	4.01	0.60		561	
	W/I	7.293	10.703	9.156	13.157	2.50	0.36		120	
Income	part	0.018	0.139	0.030	0.446	322	1.00	330	1772	2495
(determinist.)	share	0.088	0.106	0.052	0.111	6.00	0.80		587	
	W/I	7.735	9.850	10.804	15.060	1.60	0.19		136	
Income	part	0.000	0.247	0.001	0.305	256	1.00	326	1558	2080
(stochastic)	share	0.000	0.160	0.054	0.165	24.91	1.00		480	
	W/I	2.616	8.213	5.905	12.189	44.79	1.00		42	
Medical Exp	part	0.082	0.323	0.019	0.482	23.87	1.00	29	801	1435
(determinist.)	share	0.097	0.135	0.052	0.112	1.30	0.14		502	
	W/I	7.910	11.303	8.212	14.598	3.39	0.51		132	
Medical Exp	part	0.082	0.315	0.017	0.404	50.24	1.00	58	908	1558
(stochastic)	share	0.097	0.133	0.046	0.093	2.93	0.34		525	
	W/I	7.902	11.119	7.966	13.598	4.61	0.67		125	

This table reports counterfactuals from imposing US parameters (one parameter at a time) on the Chinese households, assuming households faces the completely new regime in China throughout their lifecycle. The benchmark moments are simulated from the completely new regime using parameters from the baseline model. The distance is measured by the sum of squared differences between the counterfactual moments and the moments from the benchmark model using the inverse of the variances of data moments as weights. Both the distance relative to the baseline model moments and the distance relative to US data moments are presented. The "p-value" column shows the probability of the distance being smaller than the reported distance (relative to the baseline model). The columns labeled "Total" reports the sum of distances in participation, stock share and W/I.

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