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HOUSEHOLD FINANCE IN CHINA

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ABSTRACT

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Household Finance in China*

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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 and decide on stock market participation and portfolio adjustment. The structural estimation explicitly takes into account important regime changes in China, such as the re-opening of the stock market, the privatization of the housing market and the labor market reforms 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 factors (e.g. higher costs associated with stock market participation and a lower consumption floor in China) and preferences (e.g. higher discount factors of Chinese households).

1 Introduction

Chinese households tend to save more than their US counterparts. As a result, the average wealth-to-income ratio 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 household finance patterns in the US. In doing so, 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) the low stock market participation rate, (ii) the low share of wealth in stocks conditional on participation, and (iii) the high wealth-to-income ratio.

Relative to the US household finance patterns, the low participation rate and the high wealth-to-income ratio in China, as shown in Table 1, are particularly striking. A number of contributing factors are potentially important,

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[1]The mean wealth-to-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 the Survey of Consumer Finance between 1989-2007. In the calculation households with zero income are excluded. The high wealth-to-income ratio in China reflects the high savings rate in China as studied in, e.g., Chamon and Prasad (2010) and Chamon, Liu, and Prasad (2013).

such as institutional reasons (e.g. the high income uncertainty, the weak social insurance, and the underdeveloped equity market in China) and cohort effects stemming from major regime changes experienced by the Chinese households. In addition, there may be differences in preferences of Chinese households compared to those in the US, perhaps reflecting cultural influences. This paper studies the quantitative importance of these factors.

A lifecycle model of intertemporal choices, featuring both stock market participation and portfolio adjustment decisions, is used as a framework for our analysis. Parameters are estimated via Simulated Method of Moments (SMM hereafter), exploiting the variations of household finance patterns by educational attainment and age. The estimation is challenging for a few reasons. First, substantial cohort effects exist. Chinese households have experienced significant 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 could 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 the reform took place.[2] But their financial decisions could 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 to control for cohort effects.

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 include the cohort-specific impacts of the regime changes. In 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 (state versus non-state) and region of residence (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 educational attainment. Second, education is highly correlated with other dimensions of heterogeneity. Better educated households typically live in the urban area, have higher income, and have a high employment percentage in the state sector. Nevertheless we estimate the model incorporating heterogeneity in region of residence and in sector of employment.

To understand the large differences between China and the US household finance patterns, we conduct exper-

[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.

iments that impose one country's parameters on the other. One way to do so is to impose the US parameters on the Chinese households one at a time. From this experiment, the estimated difference in the discount factors causes the largest changes to household finance moments in China. Imposing the US stock return process or stock market adjustment cost brings the simulated moments in China closest to the data moments in the US. Differences in income processes and in medical expenses are relatively unimportant.

Further, we summarize the country-specific parameters into three categories related to (i) household preferences, (ii) the financial market, and (iii) the labor market. In the counterfactual experiment where households with the Chinese preferences work in the Chinese labor market but invest in the US financial market, these households have a wealth-to-income ratio even higher than observed in the Chinese data, reaching 9.6 times that of the US households, and their average stock market participation rate exceeds 80%. If these Chinese households also work in the US labor market (hence are exposed to less income risks and protected by a higher consumption floor), their wealth-to-income ratio would fall from 9.6 times of the US households to about 3 times, but stock share in total wealth would rise significantly. For households with the US preferences that work and invest in China, their stock market participation rate is near zero, and their wealth-to-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. These experiments show that preferences play a significant role in the between-country differences, but conditions in either the labor market or the financial market are also quantitatively important.

Using the estimated model, we also study the quantitative effects of regime changes in China on household financial choices. Counterfactual analysis reveals that the structural changes in labor income processes and the housing reform have large impacts. Had households in the 2011 survey not experienced the earlier labor market conditions with low income uncertainty, their wealth-to-income ratio would be about 20% higher, and the stock market participation rate would almost double. Without the privatization of the housing market and the ensuing house price run-ups, the wealth-to-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 share in total wealth. This is important for predicting the future behavior of currently young Chinese households.

The rest of the paper is organized as follows. Section 2 presents data facts about household finance in China and compares them with US 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 impacts of the regime changes on household finance patterns and wealth distribution in China. Section 7 quantifies the factors contributing to the large differences 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, in Table 1. The top panel shows the statistics for China calculated from the 2011 wave of the CHFS. The bottom panel shows the US statistics calculated from seven waves of the Survey of Consumer Finance (SCF) between 1989 and 2007 without any control for year or housing effects. More details on the data are provided in Appendix A.1.

Since we have only one cross section of CHFS data, it is not feasible to disentangle lifecycle profiles (i.e. age effects) from cohort effects. The table presents the average values for household financial decisions for two educational attainment levels: (i) high school and below (low-edu) and (ii) beyond high school (high-edu).[4]

Table 1: Household Finance Facts by Education

Country	Edu.	Part.	Share	W/I	Share(h)	W/I(h)
CN	low-edu	0.053	0.501	1.113	0.108	13.802
		(0.003)	(0.021)	(0.094)	(0.010)	(0.892)
	high-edu	0.252	0.512	1.604	0.131	16.189
		(0.009)	(0.012)	(0.109)	(0.007)	(1.370)
US	low-edu	0.188	0.488	1.362	0.247	3.845
		(0.008)	(0.015)	(0.084)	(0.016)	(0.231)
	high-edu	0.566	0.568	2.793	0.376	4.529
		(0.004)	(0.003)	(0.046)	(0.012)	(0.106)

This table reports the participation rate, the share of stocks in household portfolio (for participants), the mean wealth-to-income ratio (W/I) for Chinese and US households by age and educational attainment. Data for China are from the CHFS (2011). Data for the US are from the SCF (1989-2007). Households whose heads have at least a high school diploma are defined as high education households In calculating share(h) and W/I(h) housing equity is included in wealth.

We focus on three dimensions of household financial decisions: (i) the stock market participation rate, (ii) the share of stocks in the household portfolio conditional on participating in the stock market, and (iii) the wealth-to-income ratio. A household is considered a stock market participant if it holds stocks either directly or indirectly through mutual funds. Throughout the paper, the calculation of the wealth-to-income ratio is based on total family income which includes the sum of family members' labor income and transfers from the government that are not needs-based.[5]

The table presents two measures of wealth: financial wealth and total wealth that is the sum of financial wealth and net housing equity. Correspondingly, 'share(h)' is the stock share relative to the total wealth while 'share' is relative to financial wealth. Likewise, 'W/I(h)' is the ratio of total wealth relative to income, while 'W/I' is defined on the basis of financial wealth.

As is well appreciated, the average wealth-to-income ratio is about 3-4 times larger in China than in the US

[4]Only 12.4% of the population is in the high education group in China based on the 2010 census data. The corresponding number is 58.9% in the US, as reported in `https://www.census.gov/content/dam/Census/library/publications/2016/demo/p20-578.pdf`. A finer breakdown by educational attainment is not feasible due to the limited observations of households with college or post-graduate education in the CHFS sample.

[5]Needs-based transfers are included in the "consumption floor" in our structural model. The wealth-to-income ratio is calculated based on after-tax income for China but before-tax income for the US. The CHFS reports after-tax income only, while the SCF reports only before-tax income.

when housing is included in wealth. Once housing is excluded from the wealth measure, the wealth-to-income ratios naturally are lower. The difference in wealth-to-income ratio across education groups is more pronounced in the US than in China. It is also noteworthy that housing is a much more important component of wealth for the Chinese households, particularly the less educated.

The stock market participation rate is much lower in China. This is the case for both education groups. In both countries the participation rises with educational attainment.

For stock market participants, the stock share in total wealth of the US households is 2-3 times that of Chinese households. Excluding housing, stock share in financial wealth is close to 50% in both countries. For both countries, the stock share rises with education.

Table 2: Household Finance in China by Total Family Income

	Part.	Share	W/I	Share(h)	W/I(h)	Home Owner-ship Rate	Age	Fraction of High-edu
bottom 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 reports household finance moments by family income in China based on the CHFS (2011). Standard errors are reported in parentheses. The statistics for the median income households are calculated as the averages of the 100 households whose income levels are closest to the median income in the sample.

Table 2 shows household finance moments in China by family income. The participation rate rises significantly with family income. However wealth-to-income ratio is the highest among households in the bottom 10 percentile.[6] The data do not show a clear correlation between income and stock share in either financial wealth or total wealth. The last column in the table shows a clear positive correlation between income and educational attainment.

The top panel of Table 3 shows household finance patterns for the state and the non-state sector workers based on 28.6% of respondents in the 2011 CHFS sample with valid information on the sector of employment. The state sector workers have a significantly higher participation rate, wealth-to-income ratio and home ownership rate on average. These patterns are similar to the difference between low and high education groups, which is not surprising given that the state sector has a much higher percentage of high education workers as shown in Table 4 below. Stock share is not significantly different between the two sectors.

The bottom panel of Table 3 summarizes household finance moments by region in China. The participation rate and wealth-to-income ratio are much higher in the urban region. The difference in stock share is small, which is likely caused by the selection effect: only wealthy or high education rural households select to participate in the

[6] This could be caused by the high degree of income variability in China – the low income households observed in the survey could have had high income earlier. In addition, the education premium was much lower prior to 2000, hence a low income household in the 2011 CHFS may have had much higher income in the 1990s and accumulated a large stock of wealth.

Table 3: Household Finance in China by Sector and Region

	Part.	Share	W/I	Share(h)	W/I(h)	Home Ownership Rate	Age
Non-state	0.145	0.498	0.76	0.124	10.03	0.76	41.73
	(0.011)	(0.009)	(0.05)	(0.006)	(0.56)	(0.01)	(0.3)
State	0.316	0.514	1.22	0.129	11.17	0.86	42.25
	(0.014)	(0.01)	(0.09)	(0.006)	(0.57)	(0.01)	(0.29)
Rural	0.027	0.468	0.72	0.118	9.43	0.94	52.25
	(0.003)	(0.006)	(0.04)	(0.003)	(1.03)	(0.004)	(0.23)
Urban	0.185	0.512	1.64	0.125	19.02	0.81	49.10
	(0.006)	(0.005)	(0.11)	(0.003)	(1.06)	(0.01)	(0.21)

This table reports household finance moments by sector of employment and region of residence. The state sector includes employees of governments, state-owned enterprises and collectively owned firms. The non-state sector includes farmers, workers in private firms, foreign firms and firms of joint ownership with foreigners. Among the 7144 households in our sample, 5103 of them do not have valid information on sector of employment. These households are dropped when we calculate the moments by sector of employment.

stock market. The home ownership rate is higher in the rural region where house prices are lower.

Table 4 reports the joint distribution of education type with either rural-urban split or split by sector of employment. Clearly, urban and state sector households are more educated. Pre-retirement households account for a larger fraction of our sample. Table 17 in Appendix A reports household finance patterns for both China and the US by age and educational attainment.

Table 4: Joint Distribution of Households in 2011 CHFS

	Rural	Urban		Non-state	State	N.A.		Pre-retirement	Post-retirement
Low-edu	2312	2229	Low-edu	548	230	3763	Low-edu	3138	1403
High-edu	389	2214	High-edu	374	889	1340	High-edu	2201	402

This table reports the joint distribution of households in 2011 CHFS by education, rural-urban status, sector of employment and age. N.A. denotes households without valid information on sector of employment. Pre-retirement households are those with house-heads aged below 60.

3 Household Dynamic Optimization

To understand the above household finance patterns, we build a dynamic optimization model of saving and portfolio choice over the lifecycle. The parameters of this model are estimated using a SMM approach for both the US and China.

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 labor market and financial market conditions for that education and country pair. For simplicity of notation the cohort index of the Chinese households is also omitted.

3.1 Basic Assumptions

Households live for T periods, working for the first $T^r < T$ periods of life. During the working phase of life, households earn stochastic income. During retirement, households receive deterministic income, but face stochastic out-of-pocket medical expenses.[7] To be clear, these exogenous processes differ across the two countries and are, in part, a source of the between-country differences in financial choices.

Households have access to two types of assets: bonds and stocks. Bonds are risk-free and perfectly liquid, but stocks are risky and illiquid in the sense that it is costly for households to enter the stock market and costly to adjust stock holdings. Thereby the model emphasizes two key discrete choices of households: participation in the stock market and adjustment of the portfolio.

Housing is bundled with the traditional risk-free and low-return assets such as bank deposits to form a composite asset, i.e. the bonds. The housing return in China has a very low standard deviation which provides justification for this bundling.[8] The implied costless housing adjustment assumption is assessed in Section 5.2 where we compare the bond change rates from the simulated data to the proportion of liquid asset in composite bond holdings in the 2011 CHFS data, and find that the liquid proportion in the composite bond is generally sufficient for households to smooth their consumption against income and medical expense shocks.

Following Cagetti (2003), for both China and the US, we assume that nondurable consumption, $\hat{c}$ and housing services h are combined through a Cobb-Douglas function, $c = \hat{c}^{1-\phi}h^{\phi}$. In this way, housing services are included in the composite consumption c.[9]

3.2 Participant

Let $\Omega = (y, m, A, R^s)$ represent the current state of the household where y and m denote income and medical expense respectively. $A = (A^b, A^s)$ summarizes the current holdings of bond and stocks respectively and R^s is the return on stocks.

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

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

for all Ω. The subscript t in the value functions denotes the age of households. Value functions are age-dependent due to the finite horizon of households in the model. For both the state variables and control variables, we omit the age subscripts but use primes to denote variables of the next period.

If the household adjusts its portfolio, it chooses the holdings of stocks and bonds to attain a value of:

[7] The importance of income uncertainty and medical expenses in explaining the high savings rate in China is explored in Chamon and Prasad (2010) and Chamon, Liu, and Prasad (2013).

[8] The standard deviations of housing return and stock return in China are 0.075 and 0.515 respectively, according to Fang, Gu, Xiong, and Zhou (2015).

[9] We set $\phi = 0.24$ and note that the value of this parameter is not important for our moments.

$$V_t^a(\Omega) = \max_{A^{b'} \geq \underline{A}^b, A^{s'} \geq 0} \left\{ (1-\beta)c^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t V_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}} \quad (2)$$

$s.t.$ (3)

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

$$TR = \max\{0, \underline{c} - (y + \textstyle\sum_{i=b,s} R^i A^i - m)\}. \quad (4)$$

where c is the current period consumption, ν_{t+1} is the death probability between age t and $t+1$. E_t denotes the expectation with respect to future income, medical expenses and stock returns. B_{t+1} is the bequest value if the household dies, and γ is the relative risk aversion. The household's future value is summarized by the term in the brackets which depends on the degree of uncertainty and risk aversion.

θ is the elasticity of inter-temporal substitution (EIS) that determines the substitutability between the current consumption the future consumption summarized in the future value. With this recursive representation following Epstein and Zin (1989) and Weil (1990), two key aspects of household choices, namely the risk aversion and the EIS, are estimated independently.[10]

The bequest value as a function of state variables is given by:

$$B(R^b A^{b'} + R^{s'} A^{s'}) = L \times (R^b A^{b'} + R^{s'} A^{s'}). \quad (5)$$

where L determines the strength of bequest motives. This bequest value is stochastic because the stock return $R^{s'}$ is a random variable. The effect of risk aversion on bequest value appears in the parameter γ in (2).

In the choice set of equation (2), $\underline{A}^b$ is the lower-bound of bonds. 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.

The F in (2) represents the cost of stock adjustment, including fees paid as well as time costs incurred. In Bonaparte, Cooper, and Zhu (2012) and Cooper and Zhu (2016), this cost is used, in part, to match portfolio adjustment rates. Although no data exists on adjustment rates for Chinese stock market participants, the stock adjustment cost leads to lower stock market participation and lower stock share for participants, therefore is identifiable.

Equation (4) is the transfer to the household that is associated with the 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-to-income ratio of relatively poor households.

A household that participates in the stock market 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

[10]As reported in Cooper and Zhu (2016), this recursive utility formulation fits the moments for the US best.

and the value is:

$$V_t^n(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b} \left\{ (1-\beta)c^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t V_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

s.t.

$$c = y + TR - m + R^b A^b - A^{b\prime} \tag{6}$$

$$A^{s\prime} = R^s A^s \tag{7}$$

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

where the 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 holdings of low-return liquid assets, then the adjustment involves housing transaction which is clearly not costless. As mentioned earlier, we assess this assumption in Section 5.2.

A participant may also choose to exit the stock market. This is likely to be optimal when a large negative shock occurs, such as an adverse income shock or medical expense shock. In this case $A^{s'} = 0$, and the value is given by:

$$V_t^x(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b} \left\{ (1-\beta)c^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t W_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

s.t.

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

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

where $W_{t+1}(\Omega')$ is the value for non-participants discussed in the coming subsection.

3.3 Non-participant

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

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

where $W_t^n(\Omega)$ is the value of remaining a non-participant and W_t^p is the value of becoming a participant.

The optimization problem of a non-participant who remains a non-participant is:

$$W_t^n(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b} \left\{ (1-\beta)c^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t W_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

s.t.

$$A^{s\prime} = 0$$

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

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

Though stocks are not held, the household can adjust its bond account to smooth consumption.

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 of participating for the first time is given by:

$$W_t^p(\Omega) = \max_{A^{b\prime} \geq \underline{A}^b, A^{s\prime} \geq 0} \left\{ (1-\beta)c^{1-1/\theta} + \beta \left[(1-\nu_{t+1}) \left(E_t V_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \nu_{t+1} \left(E_t B_{t+1}^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

s.t.

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

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

4 Quantitative Approach

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

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

$$\pounds = min_{\Theta}(M^s(\Theta) - M^d)\mathcal{W}(M^s(\Theta) - M^d)' \tag{10}$$

where $\mathcal{W}$, the weighting matrix, is the inverse of the variance-covariance matrix of the moments. Note that the discount factor, β_i, is indexed by $i = 1, 2$ where $i = 1$ is the low education group in the baseline model but it denotes rural or non-state sector households in the extended analysis.[11] The simulated moments, $M^s(\Theta)$, are calculated from data created by simulating the decision rules derived from the household optimization problem.

In the presence of stock market participation costs, the status of being a participant itself has some value. Therefore the initial allocation of assets could be important. For the US model we take as an input the joint distribution of stocks and bonds for households aged between 25-30 in the SCF. For China neither of the two

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

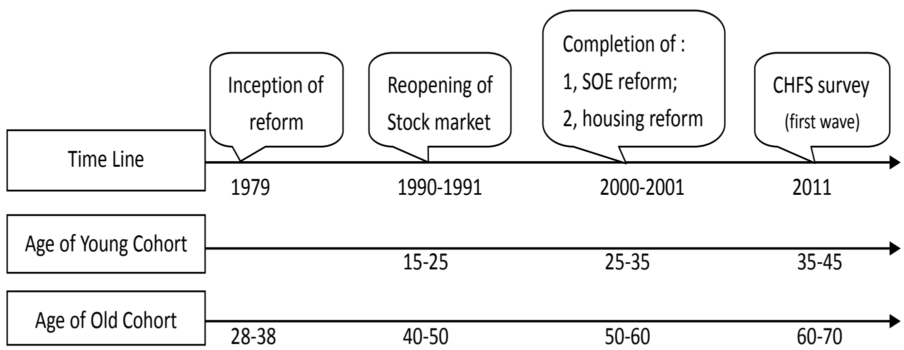
cohorts in the model has stock holdings when they enter the economy since the stock market became active only after 1990.

In computing the lifecycle optimization problem, we assume the households work for 40 years, between age 21-60 in China and 26-65 in the US. To reduce computational load we assume households die by age 91.[12]

4.1 Regime Changes

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 for cohort effects stemming from multiple regime changes in China. In our CHFS data, households have experienced regime changes at different stages of their lives, which makes the inference from a single cross section exceptionally difficult. Figure 1 lists the key regime changes and their timing.[13] We consider two cohorts in the model: a young cohort that is 35-45 years old in 2011 and an old cohort that is 60-70 in 2011. Since the two cohorts have experienced these regime changes at drastically different ages, their different household finance patterns observed in the 2011 CHFS could be attributable to cohort effects.

Figure 1: Regime Changes and Cohort Effects



This chart shows two cohorts in the 2011 CHFS and the major regime changes they experienced at different ages. These regime changes lead to cohort effects in household finance patterns observed in the 2011 survey.

When the reform began in China, the old cohort lived in a world without a stock market. The Shanghai Stock Exchange re-opened on December 19, 1990 after being closed for forty years since 1950. The Shenzhen Stock Exchange also started to operate on December 1, 1990. Thus for the old cohort the stock market was simply not accessible until they were 40 years old. However the young cohort had access to stock markets ever since they first entered the labor market.

Housing reform is another important regime change which we take into account explicitly in the estimation. Prior to housing reform there was no active residential housing market, instead houses were mostly allocated through

[12]In the Chinese 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.

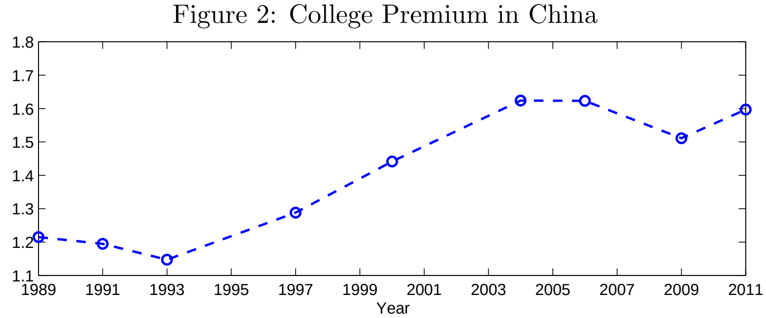
[13]Another potentially important structural change is the implementation of *the new rural cooperative medical insurance* since 2003 which provides rural households with the basic medical insurance coverage. Since the China Health and Retirement Longitudinal Study (CHARLS), the main source of medical 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.

the employment relationship rather than through market transactions. In 1998, the State Council in China issued the 23rd Decree which banned work units from developing new residential houses for their employees in any form. Households had to purchase or rent housing in the private housing market. After the reform, house prices started to take off, and the average real growth rate of house price in many cities has exceeded 10% per year since 2005. We will return to this point in Section 4.2.3 when we calibrate the return processes for stocks and bonds.

The 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 as shown in He, Huang, Liu, and Zhu (2014). By the beginning of 2000s, the SOEs had mostly been transformed into so-called "modern enterprises" that essentially maximize profits, with the freedom to set wages and layoff workers.

An obvious effect of labor market reform in China is the change of the college premium as shown in Figure 2 which uses the panel data collected in the China Health and Nutrition Survey (CHNS hereafter) between 1989-2011. The college premium rose dramatically from 1989 to 2011. This point is also evident in Figure 3 where we plot the age profiles of income estimated from the CHNS between 1989-2011. In the post-2000 era the income gap between the two education groups is clearly larger. The figure also shows a significant change in the shapes of income profiles. These structural changes dramatically separate household finance moments by the age and education groups observed in the 2011 CHFS.

Figure 2: College Premium in China



The figure shows the college premium defined as the ratio of the average labor income of individuals with college education to those without college education. Data source: the China Health and Nutrition Survey between 1989-2011.

The stochastic processes of income have also changed dramatically in China. Section 4.2.1 describes how we model and estimate the processes, and reports the related parameters in Table 5. Compared to the pre-2000 era, income shocks are both larger and more persistent after 2000. This is especially true for the more educated group. Similar changes about income risks are documented in He, Huang, Liu, and Zhu (2014).

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 opportunity. 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 enter the labor market in 1990 or later, the re-opening of the stock market does not alter their optimal decisions.

To incorporate cohort effects in the analysis, for each education group we solve the dynamic optimization problem for the two cohorts illustrated in Figure 1. For the young cohort, the stock market is always accessible, and the regime changes in the labor market and housing market occur 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 old, and the regime changes in labor market and housing market occur when they are 55. The impacts of the regime changes are reflected in household finance moments of those aged 60-70 in the 2011 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 lifecycle. There are also 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. In the estimation of the model for each country, we take these processes as exogenous inputs.

4.2.1 Income

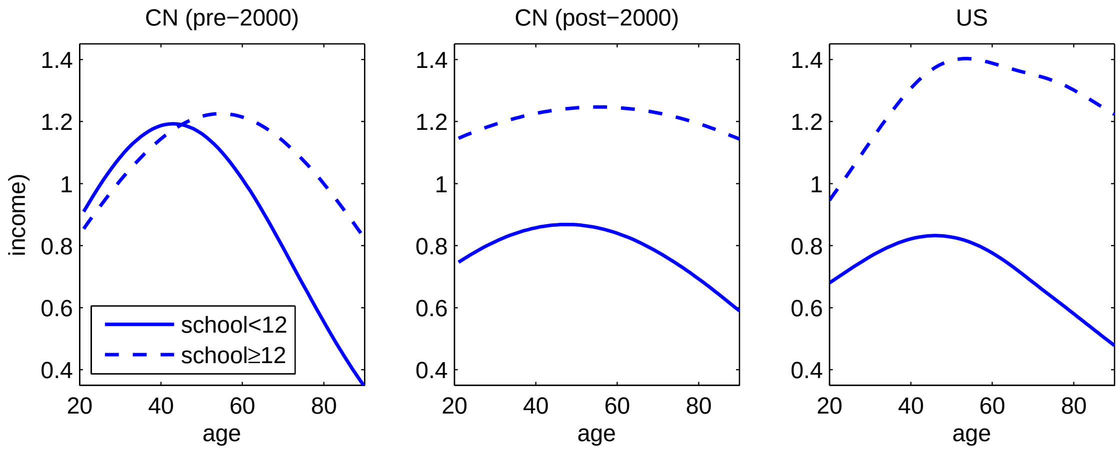
Income processes for the Chinese households are estimated using the panel data of CHNS 1989-2011. Appendix A.3 provides more details about the data. Household income is decomposed into a deterministic component and a stochastic component. For each education group, we regress the logarithm of household income on a constant, age, age-squared, year dummies (to remove aggregate shocks and growth) and a set of demographic variables, and obtain the deterministic component as the predicted income using the coefficients on age and age-squared. The stochastic component is estimated based on the regression residuals.

Deterministic Profiles: The deterministic component of income over the lifecycle are shown in Figure 3. Income levels are re-scaled so that the average of the two education groups is one. To obtain these profiles we have controlled for year effects, region of residence, gender of househead, and rural-urban status.

For China, the rising education premium is apparent.[14] 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 corresponding number is 78% in our PSID sample between 1989-2009. Therefore despite the fact that education premium has risen considerably in China, it is still small compared to the US.

[14]This is not the college premium, but the difference in income between the high education group with at least a high school diploma and the low education group with less than twelve years of schooling.

Figure 3: Age Profile of Income



The figure shows the average profiles of income by educational attainment, controlling for year effect, region of residence, gender of househead, and the urban dummy. Income levels are re-scaled so that the average of the two education groups is one.

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.

Stochastic Processes: Letting $\tilde{y}_{i,t}$ denote the residual from the income regression for household i in period t, we further decompose it into transitory and persistent shocks:

$$\tilde{y}_{i,t} = z_{i,t} + \epsilon_{i,t}$$
$$z_{i,t} = \rho z_{i,t-1} + \eta_{i,t} \tag{11}$$

where $\epsilon_{i,t}$ and $\eta_{i,t}$ are independent zero-mean random shocks, with variances σ_ϵ^2 and σ_η^2 respectively. The shock $\eta_{i,t}$ is persistent, with the persistence parameter denoted ρ.

The stochastic income process is summarized in the education-specific parameters $\{\rho, \sigma_\eta^2, \sigma_\epsilon^2\}$. 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). Table 5 reports the estimates for both China and the US, where the estimation of the US income processes are based on the Panel Study of Income Dynamics (PSID) between 1989-2009.

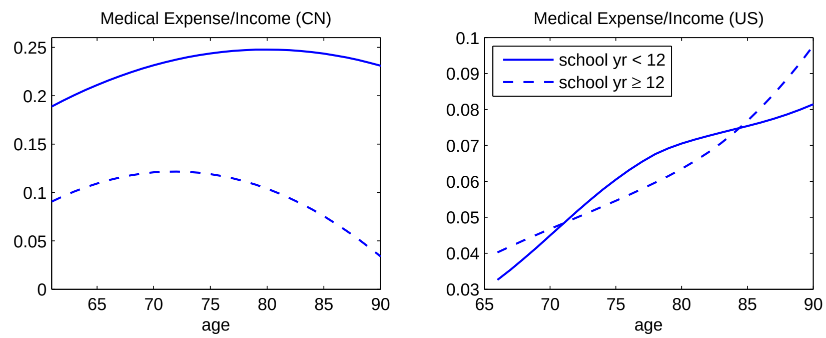
After the labor market reform in China, income shocks are more persistent and the transitory shocks are larger, which is evident in Table 5. There are also a couple of notable between-country differences. First, the variances of transitory income shocks are 3-4 times larger in China than in the US, implying 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

Table 5: 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)

This table reports the stochastic income processes based on the CHNS (1989-2011) for China and the PSID (1989-2009) for the US.

Figure 4: Post-Retirement Medical Expenses Relative to Income



The figure shows the average post-retirement profiles of out-of-pocket medical expenses relative to income by educational attainment, based on the 2011 and 2013 waves of the CHNS for China and seven waves of the Heath and Retirement Study (HRS) between 1996-2008 for the US.

times larger in China. Overall the persistent component of income shocks ($z_{i,t}$) is also more variable in China in terms of the unconditional variance of $z_{i,t}$ which is $\sigma_z^2 = \frac{1}{(1-\rho)^2}\sigma_\eta^2$ from equation (11). For the less educated group, values of ρ and σ_η^2 in Table 5 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.

4.2.2 Medical Expenses and Mortality

For China, 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 processes. More details about the data and sample selection are provided in Appendix A.3.

For each education group, we regress the ratio of out-of-pocket medical expense to income on a quadratic function of age. The left panel of Figure 4 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 based on the Health and Retirement Study (HRS) between 1996-2008, shown in the right panel. It appears that the more educated Chinese either enjoy heavily subsidized health care if they are in the state sector, or have better medical insurance coverage if they are in the private sector.

Also compared with the US households, the out-of-pocket medical expense in China has much flatter age profiles,

Table 6: Stochastic Medical Expense Processes

	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)			

The table shows the stochastic processes of out-of-pocket medical expenses, based on the 2011 and 2013 waves of the CHNS for China and seven waves of the HRS between 1996-2008 for the US.

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 is 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 6. For comparison, we also show the process for the US as 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, since their deterministic expense relative to income is much smaller, they are less vulnerable to medical expense shocks overall.

Another exogenous input in the structural model is the age-dependent death probability. For China the death probability is obtained from the mortality table based on the 2010 census, available at `http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/html/A0604a.htm`. For the US it is estimated from the HRS with the same estimation procedure as in DeNardi, French, and Jones (2010). The between-country difference is small, which is partly reflected in the average 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.[15]

4.2.3 Asset Returns

The asset returns include the returns on stocks and bonds. The latter is the weighted average of the returns on low-risk liquid assets and housing.

The real stock return includes dividends and capital gains, estimated based on the Shanghai Stock Exchange Composite Index in the period between March 1994 and March 2016.[16] The mean stock return is 10.07% with a standard deviation of 0.47. These are the statistics used in the baseline estimation. The high mean return and high standard deviation are consistent with the findings in Fang, Gu, Xiong, and Zhou (2015) that reports the mean and standard deviation of stock return to be 7.3% and 0.515 respectively for the period of 2003-2013. In the

[15] Using a similar model Cooper and Zhu (2016) finds that education-specific mortality has only marginal effects on household finance moments.

[16] Appendix A.3 provides more details.

robustness check we also estimate the model based on the (i) stock return process prior to March 2011 and (ii) stock return process of the US market explained below.

Bonds in our model are a composite of housing and the traditional low-risk liquid assets such as bank deposits and treasury bills. The real return on these traditional low-risk assets is 1.8% based on data on the real return on 1-year deposit and 90-day treasury bills as reported by People's Bank of China.[17]

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 while the standard deviation of stock returns is 0.515 during the same sample period.

A housing return of 6.28% in China is used in the baseline model. Wu, Gyourko, and Deng (2016) report an average real growth rate of house prices of 6.5% in 35 major cities. Including an annual rental return of 2%, the real urban housing return is about 8.5%.[18] In the rural area, housing transactions are limited and real house prices rarely appreciate, thus we assume a housing return of 2.5% which is the implicit rental return. In the 2011 CHFS 63% of the households are urban residents. Using this as a weight the average housing return is $8.5\% \times 0.63 + 2.5\% \times (1 - 0.63) = 6.28\%$.

In our CHFS sample, housing accounts for 81.5% of the sum of housing and the traditional low-risk assets. This ratio is 81.1% for the low education group and 80.7% for the high education group. Therefore we put a weight of 0.815 on housing and a weight of 0.185 on the traditional low-risk assets to reach a return of 5.45% for the composite bond in the baseline model.

In the robustness analysis we also consider a housing 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).[19] The corresponding composite bond has a weighted average return of 9.3%. This is an artificially high return because it does not take the low housing return in the rural area into account. Nevertheless we use it to shed light on how a lower Sharpe ratio impacts household finance moments.

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 on $S\&P500$ in the 1947-2007 period. As discussed in Cooper and Zhu (2016), in the US the return on the composite bond that also includes the traditional low-risk assets and housing is 4.08%. The Sharpe ratio (based on our definition of riskfree composite bond) 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.[20] 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 on the Chinese model, households have significantly higher stock market participation rates and

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

[18] This low rental return is consistent with Wu, Gyourko, and Deng (2012) and Wu, Gyourko, and Deng (2016). Rent-to-price ratios are generally between 2-5%. The actual rental return is even lower once vacancies and maintenance costs are taken into account.

[19] 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.

[20] Excluding housing from the bond return, the Sharpe ratio is about 0.30 for the US and 0.16 for China.

much higher stock share in total wealth.

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% which is the return on the traditional low-risk assets.

4.3 Moments

China The data moments for China are summarized in the top panel of Table 7. Here the "young cohort" and "old cohort" refer to the 35-45 and 60-70 years old households in the 2011 CHFS respectively as in Figure 1. 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, controlling for housing effects.[21] The omitted group represents households of any educational attainment in neither the 35-45 or 60-70 cohort. Using the simulated data which also contain cohort effects, we run the same regression to obtain the model moments.[22]

Note that the regression-based moments control for the effects of housing on financial decisions. Our optimization model does not include a home ownership choice. Yet, home ownership influences portfolio decisions, as shown in Cocco (2005) and Yao and Zhang (2005). Therefore in obtaining the moments of stock market participation, we include in the regression two housing related variables: a home ownership dummy and the logarithm of home equity value. By controlling for these variables the data moments are purged of their effects, hence are comparable with the model moments.

The effects of home ownership and home equity on participation are reported in Table 16 in Appendix A.2 for both China (based on CHFS) and the US (based on SCF). For both countries, home ownership is negatively correlated with stock market participation, but home equity is positively correlated with it. The table also reports a similar effect of home ownership and home equity on stock share in financial wealth.[23] These results are consistent with Chetty, Sndor, and Szeidl (2017).

As already mentioned, our optimization model includes housing wealth in the broadly defined bonds. Accordingly, the stock share moment is defined as the ratio of stock value to the total wealth: sum of financial wealth and housing wealth. This same measure of total wealth is used to calculate the wealth-to-income ratio. Thus the role of housing as a component of wealth is captured in the moments related to stock share and wealth-to-income ratio.

The US To obtain the US moments, we regress each of the three household financial decisions on a constant, age, age-squared, an education dummy, and year dummies. For the participation decision, the regression also includes a home ownership dummy and the logarithm of housing equity, with the coefficients reported in Appendix A.2.

Table 8 summarizes the data moments obtain from the regressions and used in the estimation of the parameters for the US economy. It is clear that participation, stock share and the wealth-to-income ratio are all increasing

[21] The presence of an unmarried son is also a significant regressor and its effect on wealth accumulation is consistent with Wei and Zhang (2011)), but it does not influence the moments we match.

[22] In the data moments, we adjust the constants from regressions so that the average levels of participation, stock share and wealth-to-income ratio given by the moments are the same as the simple averages in the data.

[23] The effects of home ownership and home equity on stock share in total wealth are statistically insignificant.

Table 7: Data and Model Moments for China

	const.	Young Cohort low-edu	Young Cohort high-edu	Old Cohort low-edu	Old Cohort high-edu
Data					
part.	0.120 (0.022)	−0.059 (0.010)	0.206 (0.012)	−0.059 (0.011)	0.100 (0.021)
share(h)	0.124 (0.023)	−0.002 (0.023)	0.009 (0.014)	−0.038 (0.026)	0.048 (0.025)
W/I(h)	12.478 (2.146)	−1.869 (1.109)	4.444 (1.307)	1.967 (1.200)	5.285 (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.

in educational attainment. Further, there are significant lifecycle patterns in these financial decisions which are identified from the long span of SCF data between 1989-2007.

The predicted lifecycle profiles by educational attainment are shown in Figure 5. The wealth-to-income ratios exhibit a rising trend even after retirement, consistent with DeNardi, French, and Jones (2010).

5 Estimation Results

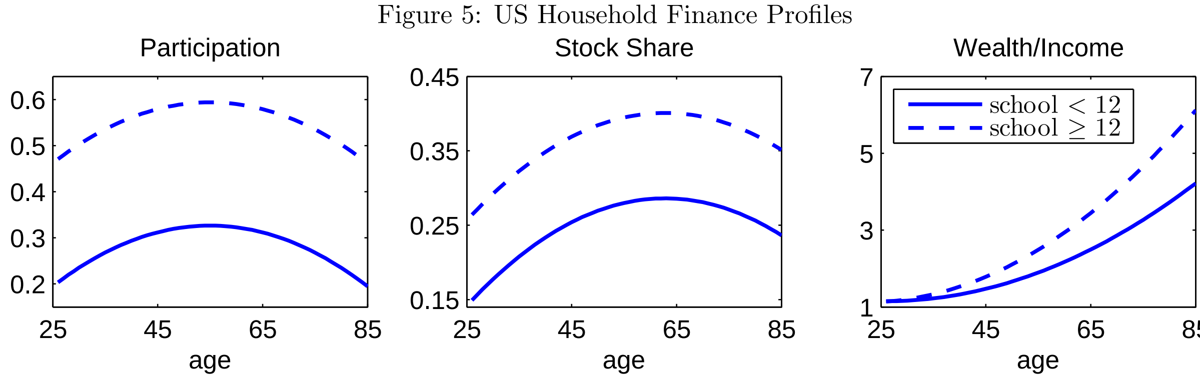
This section discusses the estimated parameters and associated moments for both China and the U.S. It then explores the robustness of these estimates. The estimation is also conducted for other sub-groups in China, based

Table 8: Data and Model Moments for the US

		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(h)	**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(h)	**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) from the data and the model. "edu" stands for the dummy for high education households. For the wealth-to-income ratio, the education dummy is interacted with age and age-squared.

Figure 5: US Household Finance Profiles



These profiles show the age dependence of household financial decisions, estimated from the SCF data between 1989-2007. The stock share and wealth-to-income ratio are calculated on the basis of the broad measure of wealth that includes financial wealth and housing equity.

on the rural-urban status or the sector of employment.

5.1 Main Results

Table 9 presents parameter estimates for both China and the US. The comparison across countries is useful for a few reasons. First, the between-country differences in household finance patterns are partly driven by these parameters. Second, the between-country comparison provides a context for evaluating the parameter estimates.

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 0.959 for the high education group. The US parameter estimates are given in the second row of Table 9. 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 γ = 7.395 in China is higher than γ=6.469 in the US, though the difference is not statistically significant due to the relative large standard errors of the two estimates.[24] For neither country is $\frac{1}{\gamma}$ close to θ as in the CRRA preference specification. The estimated bequest motives for China and the US are fairly close to each other.[25]

The estimated EIS in China is $\theta = 0.493$, significantly lower than the $\theta = 0.893$ in the US. The small estimate of the EIS in China is partly driven by the small gap in the wealth-to-income ratio between education groups. As shown in the counterfactual experiments reported in Table 14, imposing a larger EIS on China widens this gap by lowering the wealth-to-income ratio of the low education group and raising that of the high education group. Intuitively, income of the low education group falls quickly after middle age, and given a higher EIS, they care less about low consumption in the old age hence accumulate less wealth. On the other hand, for the high education households who have a large β and a relatively steeper income profile, a larger EIS induces them to sacrifice more consumption in the young age and accumulate more wealth.

The consumption floor is reported as a fraction of average household income in a country. The estimate of the floor is 7.9% of the average income in China or about 736 Yuan. This represents needs-based transfers from the government as well as among friends and relatives for which the CHFS provides some information as discussed in the Appendix. The estimated consumption floor in the US is 0.264, about 3.3 time larger than that in China. Considering the income disparity between China and the US, the gap in consumption floors is even larger in dollar value. As discussed later, this partly explains the much lower wealth-to-income ratio in the US.

The estimated cost of stock market participation is very high in China: 25.5% of the average income. The high entry cost is needed to match the relatively low stock market participation rate in China. The cost is considerably higher than the US estimate of 0.028, i.e. 2.8% of the average US household income. Using an average disposable household income of \$85 thousand for the US and \$9.3 thousand in China, the participation cost is estimated at \$2,380 in the US and \$2,375 in China, hence the costs are about the same in terms of dollar values.[26] The estimated adjustment cost of 0.051 in China is also significantly higher than a cost of 0.016 in the US, but it is actually smaller than that of the US in dollar terms.

Though we do not have any data directly related to the stock adjustment cost such as adjustment frequency, the cost is estimated precisely with a small standard error. An important source of identification is the decline in participation for the old cohort, which is evident in Table 18 in Appendix B that reports the elasticities of the simulated moments with respect to parameter values. In that table it is also clear that the wealth-to-income ratio moments are most sensitive to the discount factors. The wealth-to-income ratio moments are also quite sensitive to the consumption floor: a larger floor leads to a significantly lower ratio.

The simulated moments for China is reported in Table 7. The model matches the participation moments quite well, capturing both the effects of education and cohort. The dependence of stock share on both cohort and

[24] The estimates of γ of the two countries can be assumed to be independently and normally distributed, thus their difference has a standard deviation of $\sqrt{0.654^2 + 0.241^2} = 0.697$, and the t-stat of the difference is $(7.395 - 6.469)/0.697 = 1.33$.

[25] The bequest motive is identified through the size of wealth at old age which could be driven by purely altruism or selfish preferences. Horioka (2014) finds that bequests of the US households appear to be more consistent with altruistic preferences while those of the Chinese households appear to be more consistent with selfish preferences.

[26] The average household income in China is calculated from our sample of the 2011 CHFS which is 58,021 RMB, or about 9,313 USD using the exchange rate at the end of 2011. For the US, the 2010 wave of SCF shows that the mean and the median family income are about \$80 thousand and \$50 thousand respectively.

Table 9: 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)	
The US	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	0.940	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 on the Chinese households. β_i for $i = 1, 2$ refers to the low and high education groups except that for the "Rural-urban" case β_1 refers to rural households, and for the "Nonstate-state" case β_1 refers to households in the non-state sector.

education is relatively small in the data, and in the model. The model is unable to adequately capture the level of the wealth-to-income ratio which is the constant term in the regression, partly because this data moment has a large standard error so the minimization procedure puts less weight on it. The model does succeed in matching the higher wealth-to-income ratio for both the older and more educated households.

For the US, Table 8 presents both the data and model moments. The estimated model captures the effects of age and education on participation, share and wealth-to-income ratio fairly well. The constants of regressions are less well-fit, again because the constants are estimated with large standard errors and the SMM procedure puts less weights on matching them.

5.2 Costly Housing Adjustment

Our analysis assumes there is no cost of adjusting the composite bond which includes housing. In reality households frequently adjust their liquid assets due to various random shocks (e.g. income shocks and medical expense shocks) on the one hand, and they only adjust the holdings of housing asset occasionally on the other hand. Our assumption of costless adjustment could be too restrictive if the model-implied bond adjustment is large and exceeds the liquid assets observed in the actual data.

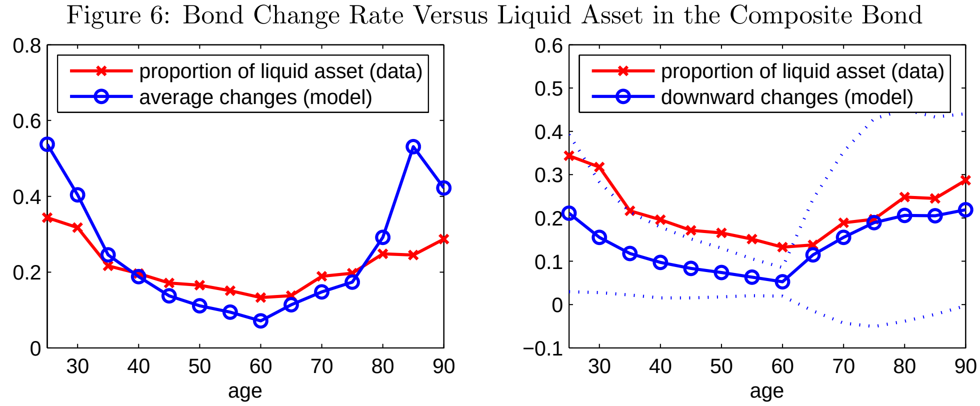
We estimate the proportion of liquid non-housing assets in the composite bond in the 2011 CHFS, and compare it with the rate of change in bond holdings in the simulated data, defined as $(A^{b\prime} - A^b)/A^b$. The purpose is to find out whether the traditional liquid asset in the data is sufficient for households in the model to buffer against shocks.

The left panel of Figure 6 shows the proportion of liquid non-housing asset in the composite bond in the 2011 CHFS by age, along with the bond change rate in the simulated data.[27] The latter is well below the former for households between ages 45 and 75, but it is well above the former before 40 and after 80.

The right panel shows downward bond change rate in the simulated data which is the average calculated from the subset of data where $(A^{b\prime} - A^b)/A^b < 0$ at each age. The downward changes are all below the proportion of liquid assets. The right panel also shows the band of one standard deviation above and below the downward change rates (dotted lines). Before the retirement age of 60, the whole band is below the proportion of liquid asset. But after retirement, the band widens considerably and goes beyond the proportion of liquid asset.

Our main concern is whether the liquid proportion in the composite bond is sufficient to buffer against income or medical expense shocks. As shown in Bonaparte, Cooper, and Zhu (2012), a important reason for households to hold bonds despite the high equity premium is to use them to buffer against shocks and smooth consumption. The above analysis shows that liquid assets are sufficient to buffer against adverse shocks. For those aged below 40 or above 80, upward bond adjustments involve housing to some extent, but these adjustments are unlikely to be responses to income or medical expenses shocks. In summary, the assumption that bonds can be adjusted without costs is not restrictive as long as its role as a buffer against income and medical expense shocks are concerned.

Figure 6: Bond Change Rate Versus Liquid Asset in the Composite Bond



The figure shows the rate of change in bonds, $(A^{b\prime} - A^b)/A^b$, in the simulated data (the circled line) against the proportion of liquid non-housing asset in total composite bond in the 2011 CHFS (the starred line). The 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 variants of the baseline model and present the results in Table 7 (moments) and Table 9 (parameters).

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

Weighting Matrix: The first exercise replaces the weighting matrix used in the baseline 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-to-income ratio becomes more important. As a result, the wealth-to-income ratio moments are better matched, but the match of moments related to participation and stock share is slightly worse.

The main features of the baseline model are preserved with this alternative weighting matrix. In particular, the large gap between the discount factors of the 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 the EIS are both significantly smaller than their US counterparts.

Stock Return Process: Given the short history of stock market in China, it is difficult to precisely measure the *expected* return and volatility of stock investment. In the baseline estimation, the stock return is estimated using the realized return of the Shanghai Stock Exchange Composite Index in the period between March 1994 and March 2016. It is likely that households form expectations about the Chinese stock market based on experiences in the developed countries like the US. It is also likely that respondents in the 2011 CHFS form expectations based on realizations prior to the survey. Therefore we carry out two related robustness exercises: (i) assuming the US stock return process; (ii) using the realized return in the period from March 1994 up to March 2011.

The row labeled "Earlier Stock Return" uses the realized stock return up to March 2011. In this case, the mean return is 12.57% and the standard deviation is 0.488. For this specification, the estimated value of adjustment cost is slightly higher, which is needed when stock return is higher in order to match the moments related to participation and stock share. Important features in China relative to the US, such as the large and highly differentiated β's, the high participation cost, the low consumption floor and the low EIS are all well preserved. The model matches 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 which are needed in order to match the moments since a higher Sharpe ratio is imposed. The fit of the model is almost five times worse than the baseline. Thus the Chinese households do not seem to form their expectation about the Chinese market on the basis of the US experiences. The difference in stock return processes is an important driver of the between-country differences in household finance patterns. This point is further substantiated in Section 7.

Housing Return: The case of "Higher Housing Return" sets the return on housing at 11% annually based on Fang, Gu, Xiong, and Zhou (2015). This increases return on the composite bond to 9.3%. In this case, the Sharpe ratio is even lower and stock investment is even less attractive, so a lower adjustment cost and a lower coefficient of risk aversion are estimated to match the participation and share moments. The high bond return also generates smaller estimates of β's and a larger consumption floor. The model fit is much worse than the baseline model, indicating that an excessively high housing return is not consistent with the expectations of households on average.

CHFS Income: There is an interesting difference between the income level from the 2011 CHFS and that from the 2011 wave of CHNS. This is shown in Table 10. The mean income levels of the young cohort are only slightly higher than the old cohort in the CHNS which is source data for income process estimation. In the CHFS data, income levels of the young cohort are significantly higher than the old cohort. The "young/old" rows show that in CHNS 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 respectively. The corresponding numbers are 1.225 and 1.638 based on the CHFS data.

The much lower income levels of the old cohort relative to the young have implications for household finance patterns. As demonstrated in Heaton and Lucas (1997) and Cooper and Zhu (2016), income substitutes for bond holdings in household's portfolio choices, and lower income of the old cohort implies a lower stock share. 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) to match their relative income observed in the 2011 CHFS, and re-estimate the model parameters.[28] The results are reported in the row labeled "CHFS Income" in Tables 7 and 9. Compared with the baseline results, now the old cohort has much lower stock share. 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 than the baseline. Most of the features of parameter estimates in the baseline, such as the large entry cost and small consumption floor, and the discount factor heterogeneity, are well preserved. However the estimated γ is smaller in order to match the participation and share moments of the old cohort who has much lower income than the young in this experiment.

Table 10: Mean Households Income in 2011 in China

	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 in 2011 from two different data sources in China: the CHFS and the CHNS.

5.4 Other Sources of Heterogeneity

As noted earlier, there are differences in household finance when comparing urban versus rural households as well as public versus private sector households. This subsection re-estimates the model based on these alternative

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

dimensions of heterogeneity.

Table 11: China: Moments by Region and Sector

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

This table reports moments from the 2011 CHFS (data moments) and the simulated data (model moments) based on heterogeneity either in region of residence or in sector of employment.

For these alternatives, the moments are created by replacing the education dummy with that based on either region of residence (rural versus urban) or sector of employment (non-state versus state), and are reported in Table 11. Comparing the data moments reported in Table 7 reveals the similarity among the splits based on education, region of residence, and sector of employment. This is not surprising since a large fraction of less educated households are rural residents and employed by the non-state sector. Nevertheless, compared with the education-based split, the gaps in stock market participation and wealth-to-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. The model moments match both the participation and stock share well. The wealth-to-income ratio is again not well matched due to the large standard errors associated with these moments.

Parameter estimates are reported in the bottom rows of Table 9. For the rural-urban split, the estimated discount factor for rural households are significantly smaller than that for urban households, and the difference is much larger than in the education-based split. The larger difference is obviously driven by the larger gap in wealth-to-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 remains.

Looking at parameter estimates based on the sector of employment, most of the parameters are close to the baseline results, but the relative risk aversion and the EIS are much smaller. The low EIS helps generate a relatively small gap in the wealth-to-income ratio between the non-state and state employees. A low γ is needed to match the share moments, especially the relatively more share holdings of the old cohort in the state sector whose wealth accumulation is not much higher than households in the non-state sector.

6 Regime Changes

This section discusses how the regime changes impact household finance moments in our single cross section. In addition, we evaluate to what extent the regime changes matter in terms of the wealth distribution in China.

Table 12: Regime Changes and Household Finance

	Young Cohort		Old Cohort		Distance	p-value	Distance
	low-edu	high-edu	low-edu	high-edu	(w.r.t. CN baseline)		(total)
Baseline Model (CN baseline)							
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	0.00	58.77
share	0.090	0.044	0.049	0.077	4.42	0.35	(p=0.00)
W/I	5.647	6.793	9.703	12.124	4.12	0.39	
New Income Process							
part.	0.084	0.691	0.051	0.394	1041	0.00	1047
share	0.089	0.082	0.073	0.105	1.32	0.86	(p=0.00)
W/I	7.459	11.003	9.085	13.689	4.60	0.33	
Old Housing Return							
part.	0.066	0.686	0.024	0.152	935	0.00	954
share	0.096	0.110	0.067	0.067	8.22	0.08	(p=0.00)
W/I	5.518	7.210	6.886	8.912	10.8	0.03	
New Housing Return							
part.	0.054	0.144	0.055	0.321	251	0.00	266
share	0.100	0.121	0.072	0.096	12.9	0.01	(p=0.00)
W/I	7.752	9.005	11.006	13.147	1.82	0.77	
Stock Market Always Accessible							
part.	0.054	0.321	0.039	0.281	13.09	0.01	13.23
share	0.093	0.071	0.066	0.076	0.12	0.998	(p=0.35)
W/I	7.326	8.549	9.759	12.009	0.02	1.00	
Completely New Regime							
part.	0.088	0.329	0.071	0.507	228	0.00	258.89
share	0.097	0.135	0.080	0.121	23.3	0.00	(p=0.00)
W/I	7.961	11.425	10.413	15.067	7.77	0.10	

This table presents moments from counterfactual experiments along with the baseline moments. The distance is measured by the sum of squared differences between the counterfactual moments and the baseline moments, weighted by the inverse of the variances of data moments. The "p-value" column shows the probability that the realized distance is even larger than the calculated distance under the null that the counterfactual model is identical to the baseline. The last column shows the total distance between moments from the baseline model and the counterfactual.

6.1 Impact on Household Finance Moments

As noted earlier, a key dimension of the analysis is the introduction of 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 in the 2011 cross section of the simulated data: young cohort with low education, young cohort with high education, old cohort with low education, and old cohort with high education. The results are shown in Table 12. As the benchmark for the experiments, the first block of the table reports statistics from the baseline model that contains cohort effects from all of the regime changes.

The first experiment imposes the old income processes, 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-to-income ratios 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 is less affected. Hence their wealth-to-income ratio is fairly close to the benchmark. In addition, for the more educated households, the deterministic income profile in the old regime falls much more quickly after retirement, which motivates them to save more for retirement, leading to a slightly higher wealth-to-income ratio in the experiment relative to the benchmark.

With the old income processes, both the participation rate and stock share are lower for each of the four groups of households. On the one hand, a lower degree of income uncertainty leads to more risk-taking hence more participation and higher stock share (the direct effect). On the other hand the lower wealth accumulation makes the entry and adjustment costs more deterring (the indirect effect). The quick decline of income with age in the old regime also causes households to take less risk, creating lower participation rates and stock shares (the substitution effect). Our quantitative results reveal that the latter two mechanisms dominate the direct effect from lower income uncertainty.

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 share in total wealth. The exceptions are the slightly lower stock share of less educated young cohort and the slightly lower wealth-to-income ratio of the less educated old cohort. The lower share is likely to be caused by the selection effect: participants become poorer (in both income and wealth) on average as more households participate in the stock market. The less educated old households have much higher income in the new income regime as shown in Figure 3, so it is not surprising they have a lower wealth-to-income ratio in this experiment.

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 changes the moments. Relative to the benchmark, the wealth-to-income ratio is much lower. The lower return on composite bond leads to a higher Sharpe ratio, thus the participation rate and the stock share are both higher for the young cohort, especially the more educated households who are subject to less income uncertainty. For the old cohort, the participation rate and stock share either decrease or remain at about the same level, thus the low wealth accumulation has a dominatingly negative effect on stock investment for the old age households, despite the higher Sharpe ratio.

Using the new housing return throughout, each group of households has a high wealth-to-income ratio due to the high return on the risk-free composite bond. Two conflicting effects arise: the lower Sharpe ratio makes stock investment less attractive, while the the larger wealth accumulation diminishes the stock market entry and adjustment costs (wealth effect). The wealth effect is weaker for the young cohorts as shown in the mild increase in wealth-to-income ratios and the lower stock market participation. But the wealth effect is strong for the old cohorts, resulting in much higher wealth-to-income ratios and participation rates.

In the block labelled "Stock Market Always Accessible", we experiment with the case when 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 decisions of the young cohort because even in the baseline model it always has access to the stock market. Among the old cohort, the less educated households are affected only slightly – with slightly higher participation rate, stock share and wealth-to-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-to-income ratio rises only slightly, implying that participants are less wealthy compared with the benchmark. As a result, the stock share (for participants) falls by about 1 percent.

In the last experiment, we assume both the young and old cohorts live throughout their lifetimes in the new regime that features relatively high income uncertainty, a high education premium, flat income profiles, a high housing return, and the access to stock market. In this experiment we see significantly higher participation rates, stock share and wealth-to-income ratios, particularly for the more educated households. The implication is that, for the new generation in China who never experience the regime changes studied in this paper, they should have even higher savings rate and be more involved in the stock market, assuming their preferences are the same as their earlier generations.

The last three columns of Table 12 report 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, and the overall distance. Specifically the distance is calculated as

$$Distance = \sum_{i=1}^{n} \left(\frac{M^i_{baseline} - M^i_{counterfactual}}{\sigma^i_M} \right)^2 \tag{12}$$

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.

Under the null that the difference $M^i_{baseline} - M^i_{counterfactual}$ follows a normal distribution with a zero mean, then the distance in (12) is a random variable (denoted x) that follows a Chi-square distribution with n degrees of freedom. This allows us to calculate the p-values defined as $Pr(x > Distance)$ which is the probability that the realization of x is even larger than the reported distance.

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 zero. 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 participation moments being 0.01), but other moments would have little changes, resulting in a overall distance of 13.25 with a p-value of 0.35. By examining the distances and p-values pertaining to participation, share and wealth-to-income ratio, it is clear that each regime change has a significant impact. But labor market reform has less impact on the stock share.

Wealth-to-income ratios are less affected by the regime changes. The less significant distance is partly caused by the high standard errors of the associated data moments. The ratios are significantly affected by the housing market reform: without the reform wealth-to-income ratios would be much lower for each group of households. Relative to the benchmark, ratios are clearly larger in the completely new regime. The impacts of changes in income process on the wealth-to-income ratio of the more educated group is also significant.

These results indicate that regime changes have significantly shaped household finance patterns in China, and it is important to take them explicitly into analysis.

6.2 Impacts on Wealth Distribution

This subsection studies how the regime changes impact the wealth distribution in China by studying various measures of wealth distribution in the simulated data from various experiments.

Table 13: Regime Changes and Wealth Distribution

	c.v. of wealth	$\frac{\text{top } 5\%}{bottom 5\%}$	$\frac{\text{top } 10\%}{bottom 10\%}$	$\frac{\text{top } 20\%}{bottom 20\%}$	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 of wealth distribution from the 2011 CHFS data, the baseline model and the counterfactual experiments.

To measure the wealth distribution, we first calculate the coefficient of variation (c.v.) of total wealth that captures the overall wealth distribution of households. However the c.v. is not very informative about the changes of distribution in tails. Therefore three additional measures are used: the mean wealth levels of top 5, 10, 20 percentiles over the corresponding bottom 5, 10 and 20 percentiles. Furthermore we report the probability of hitting the consumption floor in the simulated data.[29] A higher probability implies more households have low income and low wealth.

Table 13 reports the results. The first row reports the wealth distribution from the 2011 CHFS. 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, such as the positive correlation between wealth level and returns to wealth discussed in Fagereng, Guiso, Malacrino, and Pistaferri (2016). On average 3.63% of the households in the simulated data hit the consumption floor.

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 Process". Intuitively, the college premium is much smaller and income is much less dispersed in the old income regime due to the smaller and less persistent shocks. But the c.v. of wealth is slightly larger, indicating some rise of dispersion in the middle of the wealth distribution, which is likely to be caused by the less buffered income and medical shocks due to the reduced wealth accumulation. The probability of hitting the consumption floor falls from 3.63% to 3.01%, which reflects the thinner left tails in the income and wealth distributions.

Conversely, if households in the model face the new income processes throughout their lifetimes, the wealth distribution becomes more dispersed except that the c.v. is lowered slightly, implying fatter tails in the distribution. The probability of hitting the consumption floor also becomes higher.

With the old housing return imposed on each year in the model, the wealth dispersion increases tremendously compared with the baseline results. About 5.9% of the households 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, and the probability of hitting the consumption floor is lower. Mechanically, a higher housing return induces a higher savings rate and more wealth accumulation as discussed in the previous subsection, hence heterogeneity in income levels and income shocks becomes less relevant for wealth distribution. Notice that we assume every household participates in the housing market. If the housing market is accessible to only a fraction of households, then the implication of housing reform on wealth distribution should be different.

Accessibility to the stock market does little to change the wealth distribution, which is consistent with the fact that the Sharpe ratio is low and the stock market participation rate is low, making the accessibility to stock market less relevant for wealth distribution.

In the completely new regime, the overall wealth distribution is less dispersed and the consumption is hit with a lower probability, but both the ratio of top 5 percentile to bottom 5 percentile and the ratio of top 10 percentile to bottom 10 percentile are larger, implying that wealth distribution is polarized in the new regime.

[29] Using the simulated data, we pool households of different cohorts and ages, then calculate the probability of hitting the consumption floor as the fraction of households whose consumption equals the floor.

Based on a similar model, Cooper and Zhu (2016) studies the probability of hitting the consumption floor in the US, and finds 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 floor. Intuitively, this should be attributed to the low consumption floor and the much higher wealth-to-income ratio in China.

7 China VS the US: Why Do They Differ?

This section returns to one of the central questions of the paper: what drives the observed differences in household finance patterns between the US and China? Our paper provides an ideal framework to answer this question in the sense that the underlying driving forces are captured by country-specific parameters (e.g. discount factors, stock market entry cost, consumption floor), which facilitates counterfactual analysis.

We tackle the problem in two steps. First, we impose the US parameters on China one at a time, which highlights the relative importance of a particular parameter. Second, we group the parameters into three categories related to preferences, the financial market and the labor market respectively, and conduct experiments where households with one country's characteristics invest in another country. It is particularly interesting to see how households with Chinese preferences make financial decisions if they invest in the US financial market. The decisions clearly depend on whether the Chinese households work in the US labor market or not, which is also shown in our experiments.

Another driver of the US-China differences in household finance patterns is the regime changes that the Chinese households have experienced. We have shown the effects of regime changes in Section 6. We will return to this theme at the end of this section in the context of the US-China comparison.

7.1 Effects of a Single Parameter

We impose one US parameter at a time on the Chinese model in the absence of cohort effects, and report the simulated moments in Table 14. In the table the young households are those aged 35-45 and the old households are those aged 60-70, which is consistent with the definitions of the young and old cohorts in the model with cohort effects.

The top rows of the table shows the benchmark moments in China without cohort effects which are also moments in the "Completely New Regime" as in Table 12, and the US moments taken from the SCF data which are also reported in columns of age 35-45 and 60-70 in Table 17. We use the simulated moments as the benchmark in China because we are not able to control for cohort effects directly in the 2011 CHFS data. The distances between the counterfactual moments and benchmark moments are again calculated using equation (12), and reported in the right columns. As in the previous section, the p-values are the probability that the realized distance is even larger than the calculated distance.

The distance between the Chinese and US benchmarks is 1198. Imposing the US stock return process on the Chinese economy brings the simulated moments in China closest to US benchmark, down to 660. The stock share

Table 14: US Parameters on Chinese Households (Without Cohort Effect)

		Young		Old		Young		Old	
	edu	low	high	low	high	low	high	low	high
		CN				US			
Benchmark	part.	0.088	0.329	0.071	0.507	0.164	0.518	0.230	0.705
	share	0.097	0.135	0.080	0.121	0.240	0.376	0.221	0.371
	W/I	7.961	11.425	10.413	15.067	0.919	1.839	4.028	8.053
Imposing US Parameter						Distance (w.r.t. CN)	*Total distance*	Distance (w.r.t. US)	*Total distance*
β	part.	0.011	0.001	0.020	0.006	1399	1501	3563	4311
	share	0.083	0.077	0.060	0.032	31.06	(0.0)	725	(0.0)
	W/I	5.269	3.749	6.438	5.091	71.43		23	
γ	part.	0.072	0.317	0.070	0.505	3.68	4.5	667	1235
	share	0.108	0.136	0.090	0.125	0.40	(0.97)	449	(0.0)
	W/I	7.469	11.121	9.968	14.923	0.39		117	
θ	part.	0.035	0.527	0.032	0.932	721	741	607	1162
	share	0.090	0.146	0.073	0.195	9.55	(0.0)	394	(0.0)
	W/I	6.565	13.860	9.742	19.750	9.82		161	
L	part.	0.086	0.326	0.066	0.496	0.57	0.6	637	1232
	share	0.097	0.135	0.080	0.118	0.01	(1.0)	465	(0.0)
	W/I	7.954	11.399	10.287	14.904	0.02		130	
Γ	part.	0.412	0.820	0.113	0.626	2775	2792	1381	2158
	share	0.049	0.087	0.083	0.104	16.93	(0.0)	638	(0.0)
	W/I	8.090	11.772	10.537	15.202	0.10		139	
F	part.	0.110	0.355	0.168	0.870	387	391	306	971
	share	0.087	0.128	0.049	0.086	3.78	(0.0)	352	(0.0)
	W/I	7.976	11.458	10.489	15.184	0.008		133	
$\underline{c}$	part.	0.071	0.319	0.036	0.473	16.33	25 795	1347	
	share	0.098	0.136	0.097	0.119	0.41	(0.01)	457	(0.0)
	W/I	6.830	11.238	7.291	14.715	7.78		96	
Return (stock)	part.	0.085	0.354	0.114	0.736	138.31	247	361	660
	share	0.196	0.228	0.198	0.241	106.22	(0.0)	143	(0.0)
	W/I	8.054	12.094	10.964	18.040	2.28		156	
Return (bond)	part.	0.094	0.338	0.051	0.481	5.75	12	653	1299
	share	0.093	0.114	0.088	0.091	4.01	(0.45)	554	(0.0)
	W/I	7.293	10.703	9.156	13.157	2.50		102	
Income (determinist.)	part.	0.018	0.139	0.030	0.446	322	330	1692	2376
	share	0.088	0.106	0.052	0.111	6.00	(0.0)	567	(0.0)
	W/I	7.735	9.850	10.804	15.060	1.60		117	
Income (stochastic)	part.	0.000	0.247	0.001	0.305	256	326	1570	2058
	share	0.000	0.160	0.054	0.165	24.91	(0.0)	455	(0.0)
	W/I	2.616	8.213	5.905	12.189	44.79		32	
Medical Exp (determinist.)	part.	0.082	0.323	0.019	0.482	23.87	29	810	1406
	share	0.097	0.135	0.052	0.112	1.30	(0.004)	484	(0.0)
	W/I	7.910	11.303	8.212	14.598	3.39		113	
Medical Exp (stochastic)	part.	0.082	0.315	0.017	0.404	50.24	58	936	1550
	share	0.097	0.133	0.046	0.093	2.93	(0.0)	507	(0.0)
	W/I	7.902	11.119	7.966	13.598	4.61		107	

This table reports counterfactuals from imposing US parameters (one at a time) on the Chinese model, controlling for cohort effects. The CN benchmark are simulated from the completely new regime using parameters from the baseline model. The US data moments are taken from the SCF data between 1989-2007. The columns labeled "Total" reports the sum of distances in participation, stock share and W/I.

rises significantly for each of the age and education group. Thus the low Sharpe ratio in the Chinese financial market is an important driver of the US-China differences in household finance. With the higher Sharpe ratio, stock market becomes more attractive, therefore the participation rate and wealth-to-income ratio are also higher.

Imposing the US stock market adjustment cost on China lowers the distance with respect to the US data from 1198 to 971. The gain mainly comes from the higher stock market participation rate in China resulting from the low adjustment cost estimated in the US model. As shown in the table, the moments associated with participation have a distance of 614 in the benchmark model as opposed to a distance of 433 when the US stock adjustment cost is imposed.

Based on the distance with respect to the Chinese benchmark, discount factors and the stock market entry cost change the simulated moments form China the most. Imposing the US discount factors on China causes the wealth-to-income ratio to fall by 33-66% for different groups of households.[30] The difference made by the entry cost is also clear: imposing the US entry cost on China causes the participation rate of the high education old households in China to rise by 24%, and the low education young households by 368%. Although these parameters cause big changes to the Chinese moments, they actually widen the US-China household finance disparity, which is evident by comparing the distance with respect to the US data.

When the US value of θ is imposed on the Chinese economy, wealth-to-income ratios are lowered for the less educated Chinese but raised for the more educated. With the larger θ, households are more willing to substitute inter-temporally and care less about the rises and falls of consumption over lifecycle, which causes the lifecycle profile of wealth to track that of income more closely. For the more educated Chinese, the decline of income occurs later and to a less extent as shown in Figure 3, hence their wealth-to-income ratio is raised by a larger θ, while the wealth-to-income ratio of the less educated are lowered. Overall the US-China gap in household finance is not changed.

In the experiment where we impose the US consumption floor on the Chinese households, the wealth-to-income ratios are lowered. This effect is particularly strong for the young households who are more likely to use the consumption floor due to their relatively low wealth levels. In the simulated data the average probability of hitting the consumption floor is 7.93% compared with 3.46% in the benchmark model. With the reduced wealth accumulation households participate less in the stock market. The stock share moments are little changed. As shown in the last two columns of the table, the experiment widens the US-China gap in terms of the participation moments, leading to a greater overall deviation of the model moments in China from the data moments in the US.

Table 14 also indicates the roles played by the high variability of income in China. Imposing the US stochastic income on China, the low education households on average lower their wealth-to-income ratio by more than 50% and their stock market participation rate is near zero. The high education households also reduce their wealth accumulation and stock market participation significantly.

Since we assume the out-of-pocket medical expense occurs only after retirement, imposing the US process on China mainly affects the old households. Both the stochastic medical expense and deterministic profiles from the

[30] This contrasts with Carroll, Rhee, and Rhee (1994) that concludes that cultural difference has little effect on savings behavior by examining the marginal propensity to consume of immigrants in Canada from different cultures.

US cause households to reduce their post-retirement stock market participation, stock share and wealth-to-income ratio significantly.

7.2 Chinese in the US VS Americans in China

Having studied the country-specific parameters individually, we break them into three determinants of US-China differences in household finance, related to: (i) preferences, (ii) the financial market and (iii) the labor market. We define households as Chinese (Americans) if they have preferences estimated from the Chinese (US) model, including the discount factors (β's), risk aversion (γ), EIS (θ) and bequest motives (L). Presumably these are deep parameters that do not change even if a household migrates from one country to another.

A country's financial market is characterized by its bond return, stock return process, and stock market entry cost and adjustment cost. In our model the underdeveloped financial market in China relative to the US is reflected in the high entry and adjustment costs, and a highly volatile stock market with a low Sharpe ratio.

A country's labor market is characterized by its consumption floor, income processes, and medical expense processes. The labor market in China features a large degree of income uncertainty and an underdeveloped social safety net (a low $\underline{c}$).

Table 15: Cross-country Counterfactuals

	Counterfactual				**Benchmark**			
	Young		Old		Young		Old	
	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	0.164	0.518	0.230	0.705
share	0.253	0.267	0.172	0.192	0.240	0.376	0.221	0.371
W/I	7.629	12.047	10.036	16.175	0.919	1.839	4.028	8.053
	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 reports four counterfactuals experiments (the left panels) and the benchmarks (the right panels). A Chinese is defined as a household with the preference parameters estimated from the Chinese model, including discount factors (β's), risk aversion (γ), EIS (θ), and bequest motive (L). An American is 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.

Four experiments are conducted: (i) Chinese in the US financial market, (ii) Chinese in the US financial market and labor market, (iii) Americans in the Chinese financial market, and (iv) Americans in the Chinese financial market and labor market.[31] The first two experiments are about Chinese in the US, and the last two about Americans in China.

Chinese in the US: In the experiment of 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 relative to the average income in China on the basis that the literature generally interprets the costs as information and time costs rather than direct monetary costs.[32] Similarly for Americans investing in China but working in the US, their costs are relative to their labor income in the US.

Results are reported in Table 15. On the left side are moments from the counterfactual experiments and on the right side are the benchmarks. The US benchmark is from the SCF data while the Chinese benchmark is from simulating the model without regime changes (the completely new regime).

For the Chinese in the US financial market but not the US labor market, the stock market participation rate is close to 100%, except that the less educated old households has a participation rate of 70.9%. The wealth-to-income ratio of the Chinese households is much higher than the US counterparts, especially for the young households. Stock share of these Chinese is still lower than the US households, but much higher than the share observed in the Chinese data. Intuitively, the Chinese accumulate massive wealth because of their large discount factors and strong precautionary motives caused by the highly variable income, the large coefficient of risk aversion and the small consumption floor. Such wealth levels make the low costs in the US financial market negligible, leading to the extremely high participation. This experiment makes it clear that country-specific preferences are an important determinant in the US-China difference, particularly for moments associated with the wealth-to-income ratio.

If the Chinese households not only invest in the US financial market, but also work in the US labor market, then their market participation rate and wealth-to-income ratio are still significantly higher than the US counterparts, but lower than the Chinese who only invest in the US financial market. This is because the latter is subject to more labor market uncertainty and faces a low consumption floor, hence needs more precautionary savings. The latter also has lower stock share on average, which partly reflects the less risk-taking due to labor market uncertainty and a low consumption floor. Evidently, the under-developed financial market and labor market in China are quantitatively important in determining the low stock market participation rate and the low stock share in wealth

[31] This paper does not consider cross-country asset allocation. For example, for Chinese households investing in the US financial market, we assume they have no investment in China. The results here are based solely on simulations using estimated parameter values.

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

in China.

Americans in China: Turning to the case of Americans in China, if the US households invest in the Chinese financial market but do not work in the Chinese labor market, their stock market participation rate is zero, and on average they accumulate less wealth than Americans in the US financial market. For the US households who both work and invest in the Chinese markets, the stock 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-to-income ratio is significantly higher than Americans who invest but do not work in the Chinese markets.

Clearly each of the above three determinants is at work. First, the low discount factors and low coefficient of risk aversion of the US households lead to much lower wealth accumulation. Second, the high costs and low Sharpe ratio in the Chinese financial market keep the US households, who do not accumulate much wealth, from investing in the stock market. Third, the high labor market risks and low consumption floor in the China lead to more wealth accumulation, which explains why the US workers in China have higher wealth-to-income ratios than the US investors in the Chinese financial market.

7.3 Regime Changes and the US-China Differences

As discussed earlier, the regime changes experienced by the Chinese households also contribute to the between-country differences in household finance patterns. This point is supported by comparing Tables 19 that includes cohort effects with Table 14 that excludes cohort effects. Both tables present the distances between the Chinese model moments and the US data moments (the last column). 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.

8 Conclusions

This paper has studied household financial decisions for different education and age groups in China, and compares them with US households. Patterns of household finance, including participation in the stock market, stock share in total wealth, and wealth-to-income ratio, are studied jointly by estimating and simulating a lifecycle optimization model. This broadens the analysis beyond the dimension of the high savings rate in China.

One key point of the analysis is to uncover to what extent the major regime changes in the labor market and financial market in China have impacted household finance patterns observed in the data. Counterfactual experiments reveal that the higher income uncertainty resulting from labor market reforms has significantly increased the wealth accumulation of the Chinese households, which in turn raised stock market participation and the share of stocks in total wealth. The high return on housing investment after the housing reform has also boosted wealth accumulation, but it has lowered stock market participation for the young households. The inaccessibility of stock market prior to 1990 has only marginal impact on household finance patterns observed in the 2011 data.

Another important point of the analysis is to understand why household finance patterns differ between China and the US. A comparison of parameters shows that, relative to the US, households in China have preferences with more patience and less willingness to substitute their consumption inter-temporally. They also face an underdeveloped financial market with a lower Sharpe ratio and higher costs associated with the stock market, and face a labor market with more variable income and a low consumption floor. We analyze the roles of the difference in parameters in two steps. The first step is to impose one US parameter on the Chinese model at a time. We find that imposing the US stock market return process or the US stock adjustment cost on China brings the simulated moments in China closest to the data moments in the US. Imposing the US discount factors on Chinese households causes the largest changes to the simulated moments in China but significantly widens the disparity in household finance moments between the two countries.

In the second step the parameters are grouped into three categories related to (i) household preferences, (ii) the financial market, and (iii) the labor market, respectively, which facilitates the experiments where households with one country's characteristics invest in another. We find that preferences are the most important driver of the large disparity in wealth-to-income ratio between the two countries, while institutions (financial market and labor market) are quantitatively important in explaining the large between-country differences in stock market participation and stock share in total wealth.

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 the 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.

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Appendices

A Data Appendix

A.1 CHFS data

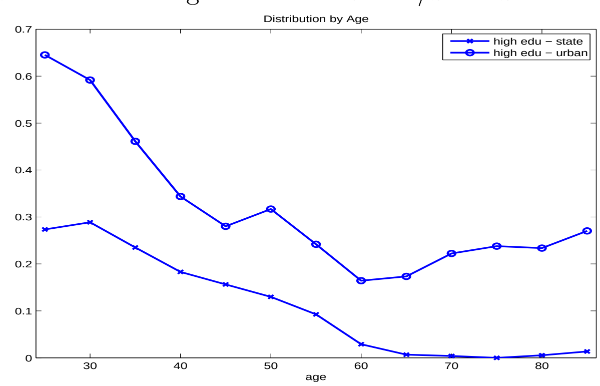
The key data set for this study is the 2011 wave of China Household Financial Survey (CHFS). The CHFS is conducted by the Survey and Research Center of China Household Finance, Southwestern University of Finance and Economics, Chengdu, China. Gan, Yin, Jia, Xu, Ma, and Zheng (2013) provides a comprehensive description of the survey and some key statistics found in the survey.

Detailed information about the CHFS is available at `http://www.chfsdata.org/`. For each household in the sample, the survey identifies a respondent which is defined as the member who knows the best about a household's financial situation. For 86.22% of the households in the survey, the respondents and their spouses make decisions regarding stock market investment according to question [D3112] in the survey. A household is considered a stock market participant if it holds stocks either directly or indirectly or both. Direct stockholding information is provided in questions [D3101] and [D3103]. Indirect holding is through mutual funds that invest mainly in the equity market, with related information obtained in answers to questions [D5104] and [D5107].

The data have some information about transfers. About 5% of the respondents live in a house that is 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. Among households who receive transfers, the average government transfer is 1582 Yuan and the average private transfer is 4298 Yuan.

We split the CHFS sample in three alternative ways based on: (i) educational attainment; (ii) region of residence (rural versus urban); and (iii) sector of employment (non-state versus state). The state sector households include those employed by the governments, the SOEs and the collectively-owned enterprises. The joint distribution of households is reported in Table 4. Figure 7 plots the fraction of high education urban households and the fraction of high education state sector employees against age. These fractions are clearly larger among the young.

Figure 7: Fraction of high education Urban/State-Sector Employees



This figure plots the fraction of high education households that live in the urban area or are employed by the state sector in the 2011 CHFS.

A.2 Housing and Portfolio Choice

Table 16 shows that housing has statistically significant effects on stock market participation and stock share in financial wealth in both China and the US.

A.3 China: Exogenous Processes

Returns: Stock return process is calculated based on Shanghai Stock Exchange Composite Index, available from WIND 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 compounds them into annual returns. Between March 1994 - March 2016, the annualized mean return is 10.07% with a standard deviation of 0.47. These statistics are used in the baseline model. Since the CHFS survey is done in 2011, it is likely that households form expectations about stock return based on realizations prior to the survey, therefore we also estimate the stock return process based on the earlier years: between March 1994 -

Table 16: Effects of Home Ownership and Home Equity on Portfolio Choices

China		Young Cohort		Old Cohort		**Homeowner**	**Home Equity**
	const.	low-edu	high-edu	low-edu	high-edu		(*logarithm*)
part.	0.120	-0.059	0.206	-0.059	0.100	-0.113	0.010
(s.e.)	(0.022)	(0.010)	(0.012)	(0.011)	(0.021)	(0.014)	(0.001)
share	0.503	-0.041	0.024	0.029	0.036	-0.013	0.003
(s.e.)	(0.047)	(0.039)	(0.024)	(0.046)	(0.043)	(0.034)	(0.002)
US	const.	age	age^2	high-edu			
part.	-0.116	0.0161	-0.00015	0.267		-2.276	0.112
(s.e.)	(0.073)	(0.0012)	(0.00001)	(0.010)		(0.057)	(0.002)
share	0.275	0.0093	-0.00009	0.056		-0.144	0.007
(s.e.)	(0.071)	(0.0013)	(0.00001)	(0.014)		(0.052)	(0.002)

This table reports coefficients from regressing portfolio decisions on age and education dummies, the home ownership dummy and logarithm of home equity, based on the CHFS 2011 for China and the SCF between 1989-2007 for the US. Here "share" is the share of stocks in financial wealth.

March 2011. The resulting annualized mean return is 12.57% with a standard deviation of 0.488. The difference in mean returns is partly due to the stock market crash in June 2015. 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. 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 wealth in the portfolio. Among the three major categories of asset (bond, stock, housing equity), the share of housing wealth is 80% on average based on the 2011 CHFS. Excluding stock, housing wealth accounts for 88.1% of the sum of housing wealth 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.

The housing market started to be marketized since the end of 1990s. House price 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, non-RMB asset, and cash lent to friends and relatives. Collectively these assets are named bonds in this paper.

Consistent with our definition of bond, bond return is the weighted average of housing return and 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%.[33] We include

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

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.[34] 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. Wu, Gyourko, 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%. Wu, Gyourko, 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 on 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. In the robustness check 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 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, educational attainment, occupation, region of residence and sector of employment. We use these demographic variables to filter out predictable component of income. The survey consistently constructs nine 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, educational attainment, region of residence and sector of employment.

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

The following households are excluded: (i) households that report 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 the medical expense 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 conducted by the National School of Development at Peking University

Since 2011 the survey collects a representative sample of Chinese age 45 and older every two years. The survey data contain information on household demographics, health status, health care expenses, health insurance coverage, 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 and hence the definitions of out-of-pocket medical expenses are highly comparable.

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 (ED007), transportation cost to medical facilities (ED015 and EE015), total treatment and medication cost (ED023), self-paid treatment and medication cost (ED024), total hospitalization cost (EE005) and the self-paid part (EE006), total self-treatment cost (EF002) and the self-paid part (EF003), total cost of dental care (EH003) and the self-paid part (EH004). We drop respondents without valid information on age, educational attainment, gender, hukou (rural versus urban), and sector of employment.

A.4 US Data

We estimate the US household finance patterns based on seven wave of Survey of Consumer Finance between 1989-2007. We use the same sample selection criteria and definition of stock holdings as in Cooper and Zhu (2016) which studies US household finance patterns by a finer breakdown of educational attainment.

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).

Table 17 shows the difference in household finance patterns between US and China by age and educational attainment which supplements Table 1. It's noteworthy that wealth-to-income ratio rises more sharply in old age in the US than in China.

Table 17: Household Finance Facts by Education and Age

Age	25-34		35-45		46-59		60-70		71-80	
Edu	low	high	low	high	low	high	low	high	low	high
China										
part.	0.075	0.272	0.057	0.333	0.052	0.191	0.051	0.228	0.031	0.164
	(0.015)	(0.019)	(0.007)	(0.017)	(0.006)	(0.013)	(0.007)	(0.027)	(0.009)	(0.033)
share	0.368	0.453	0.460	0.525	0.542	0.534	0.534	0.538	0.502	0.505
	(0.072)	(0.025)	(0.039)	(0.019)	(0.035)	(0.022)	(0.047)	(0.040)	(0.093)	(0.056)
share(h)	0.138	0.134	0.119	0.130	0.098	0.116	0.083	0.169	0.103	0.132
	(0.041)	(0.017)	(0.020)	(0.012)	(0.017)	(0.010)	(0.013)	(0.028)	(0.043)	(0.043)
W/I	1.919	1.330	1.229	1.806	0.944	1.394	0.999	2.257	1.178	1.334
	(0.615)	(0.191)	(0.179)	(0.221)	(0.051)	(0.112)	(0.117)	(0.392)	(0.242)	(0.165)
W/I(h)	15.30	10.17	10.43	19.80	12.95	16.24	17.67	17.58	16.46	14.86
	3.454)	(1.070)	(0.831)	(1.716)	(0.501)	(0.734)	(1.389)	(1.860)	(1.900)	(2.030)
US										
part.	0.081	0.361	0.164	0.518	0.213	0.665	0.230	0.705	0.215	0.634
	(0.017)	(0.009)	(0.020)	(0.007)	(0.018)	(0.006)	(0.019)	(0.009)	(0.020)	(0.013)
share	0.509	0.515	0.564	0.567	0.522	0.586	0.471	0.580	0.439	0.542
	(0.071)	(0.010)	(0.044)	(0.006)	(0.031)	(0.005)	(0.031)	(0.007)	(0.032)	(0.010)
share(h)	0.351	0.341	0.240	0.376	0.263	0.389	0.221	0.371	0.229	0.361
	(0.076)	(0.024)	(0.086)	(0.035)	(0.025)	(0.022)	(0.022)	(0.008)	(0.024)	(0.009)
W/I	0.120	0.586	0.322	1.155	0.582	2.753	1.400	5.128	2.577	7.541
	(0.022)	(0.044)	(0.053)	(0.047)	(0.054)	(0.076)	(0.174)	(0.148)	(0.243)	(0.287)
W/I(h)	0.297	0.874	0.919	1.839	2.233	4.536	4.028	8.053	6.988	12.49
	(0.108)	(0.133)	(0.114)	(0.300)	(0.193)	(0.110)	(0.347)	(0.217)	(0.624)	(0.638)

This table reports the participation rate, the share of stocks in household portfolio (for participants), the mean wealth-to-income ratio (W/I) for Chinese and US households by age and educational attainment. Data for China are from the CHFS (2011). Data for the US are from the SCF (1989-2007). Households whose heads have at least a high school diploma are defined as high education households In calculating share(h) and W/I(h) housing equity is included in wealth.

B Elasticity of Moments to Parameters

Table 18 reports the elasticities of simulated moments from the baseline model with respect to the estimated parameters.

Table 18: Elasticity of Moments to Parameters

		Young Cohort		Old Cohort	
	const.	low-edu	high-edu	low-edu	high-edu
			Participation		
β_1	0.984	3.105	-0.984	-0.007	-0.984
β_2	4.751	-4.751	11.435	-4.751	13.628
Γ	-0.109	0.109	0.571	0.109	-1.368
F	-18.125	13.559	-19.437	15.814	-27.868
γ	-0.005	-0.002	0.016	0.007	-0.034
θ	-0.217	-1.332	0.867	0.110	-0.593
$\underline{c}$	-0.145	0.096	0.097	0.422	-0.050
L	-0.050	-0.077	-0.034	0.047	-0.113
			Share		
β_1	0.091	0.667	-0.091	-0.334	-0.091
β_2	0.168	-0.168	-0.218	-0.168	-0.609
Γ	0.010	-0.010	-0.035	-0.010	0.094
F	8.382	-5.784	-7.011	-5.868	-7.064
γ	0.010	0.000	-0.010	-0.013	-0.012
θ	0.337	-0.576	-0.271	-0.263	-0.377
$\underline{c}$	0.606	-0.594	-0.610	-0.449	-0.638
L	0.040	-0.111	-0.042	-0.038	-0.045
			W/I		
β_1	19.521	49.545	-19.521	42.241	-19.521
β_2	26.379	-26.379	31.747	-26.379	46.656
Γ	-0.119	0.119	0.206	0.119	-0.627
F	0.050	0.675	-5.878	0.964	-2.964
γ	0.308	1.095	-0.092	0.207	-0.175
θ	-0.187	-18.962	4.152	3.609	3.340
$\underline{c}$	-6.031	-3.327	5.029	-1.491	5.307
L	-0.968	-0.467	0.776	-3.167	0.645

Each row of the table reports the elasticities of simulated moments from the baseline model with respect to one estimated parameter.

C Counterfactuals With Cohort Effects

Table 19 reports results from imposing US parameters on the Chinese model in the presence of cohort effects.

Table 19: US Parameters on Chinese Households (With Cohort Effects)

		Young		Old		Young		Old	
	edu	low	high	low	high	low	high	low	high
		CN				US			
Benchmark	part.	0.054	0.321	0.037	0.205	0.164	0.518	0.230	0.705
	share	0.093	0.071	0.065	0.085	0.240	0.376	0.221	0.371
	W/I	7.326	8.549	9.718	11.723	0.919	1.839	4.028	8.053
Imposing US Parameter						Distance (w.r.t. CN)	$Total$ $distance$	Distance (w.r.t. US)	$Total$ $distance$
β	part.	0.006	0.0001	0.006	0.002	842	890	3650	4353
	share	0.095	0.090	0.060	0.029	6.91	(0.0)	681	(0.0)
	W/I	5.042	3.273	6.146	4.217	40.7		21	
γ	part.	0.056	0.398	0.038	0.205	40.9	41	1087	1845
	share	0.087	0.069	0.074	0.088	0.22	(0.0)	684	(0.0)
	W/I	6.901	8.247	9.260	11.476	0.36		74	
θ	part.	0.018	0.771	0.009	0.835	2320	2339	1100	1825
	share	0.099	0.072	0.064	0.146	6.17	(0.0)	626	(0.0)
	W/I	5.970	10.703	8.443	17.709	12.62		99	
L	part.	0.052	0.313	0.034	0.197	0.75	0.80	1319	2085
	share	0.094	0.072	0.065	0.082	0.01	(1.0)	682	(0.0)
	W/I	7.348	8.522	9.578	11.584	0.02		83	
Γ	part.	0.453	0.764	0.089	0.458	3125	3132	1564	2410
	share	0.042	0.064	0.088	0.057	7.13	(0.0)	755	(0.0)
	W/I	7.556	8.847	9.943	12.067	0.15		92	
F	part.	0.134	0.679	0.102	0.496	1178	1181	423	1264
	share	0.064	0.065	0.046	0.057	3.51	(0.0)	754	(0.0)
	W/I	7.380	8.715	9.770	11.897	0.03		87	
$\underline{c}$	part.	0.043	0.300	0.014	0.166	12.24	22	1519	2246
	share	0.090	0.071	0.084	0.083	0.56	(0.04)	676	(0.0)
	W/I	6.114	8.220	6.282	10.952	9.49		51	
Return (stock)	part.	0.056	0.264	0.083	0.410	136	231	938	1364
	share	0.185	0.156	0.218	0.153	94.8	(0.0)	328	(0.0)
	W/I	7.526	8.957	10.423	13.023	0.82		98	
Return (bond)	part.	0.066	0.463	0.028	0.176	144	146	1090	1840
	share	0.086	0.075	0.080	0.071	0.81	(0.0)	680	(0.0)
	W/I	6.827	8.209	8.829	10.517	1.11		69	
Income (determinist.)	part.	0.007	0.304	0.003	0.246	38	41	1469	2286
	share	0.089	0.056	0.041	0.088	2.20	(0.0)	743	(0.0)
	W/I	6.910	8.380	8.830	12.834	0.95		75	
Income (stochastic)	part.	0.000	0.307	0.001	0.219	42	94	1546	2175
	share	0.032	0.094	0.040	0.151	17.49	(0.0)	613	(0.0)
	W/I	2.452	6.427	5.596	9.674	34.38		16	
Medical Exp (determinist.)	part.	0.049	0.310	0.008	0.158	13	17	1520	2285
	share	0.094	0.071	0.044	0.081	0.69	(0.15)	695	(0.0)
	W/I	7.293	8.392	7.785	11.025	2.68		69	
Medical Exp (stochastic)	part.	0.049	0.301	0.008	0.100	35	41	1694	2481
	share	0.094	0.070	0.040	0.061	1.87	(0.0)	721	(0.0)
	W/I	7.292	8.149	7.563	9.661	4.15		65	

This table reports counterfactuals from imposing US parameters (one parameter at a time) on the Chinese model without controlling for cohort effects. The distance and p-value (reported in parentheses) are defined as in Table 14.