A MODEL FOR STRESS TESTING HOUSEHOLD SECTOR IN MONGOLIA

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Abstract

This paper outlines a simulation-model for stress-testing household sector in Mongolia. The model uses data from the Household Socio-Economic Survey (HSES) to assess the financial resilience of households to macroeconomic shocks. The model suggests that the household sector is vulnerable to scenarios involving interest rate, basic consumption price, asset price and unemployment rate shocks, and the associated increases in household loan losses due to interest rate and basic consumption price shocks are considerable. The results show that substantial increase in household indebtedness has increased the household sector's financial fragility. This paper provides a useful starting point for the development of a more holistic stress-testing framework for the Mongolian banking system.

Keywords: Stress tests, household indebtedness, household surveys, Mongolia.

JEL classification: D14, C15, D31, E17.

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1. Introduction

The recent global economic crisis has emphasized a risk that the household sector can lead to financial instability, and consequently to a deeper and longer economic recession. High levels of household debt raise the vulnerability of household balance sheets to macroeconomic shocks (i.e., shocks to income, asset prices, and interest rate). Adverse shocks deteriorate households' ability (or willingness) to repay their debts, and thereby could have a strong negative impact on the financial health of lenders. As a result, household debt could amplify downturns and weaken economic recoveries (IMF 2012).

The recent rise of household indebtedness has shaped concerns about the vulnerability of households to macroeconomic shocks and the impact on macro-financial stability in Mongolia. The financial system's lending to households accounts for a sizeable share of its total lending exposures which is averaged at 40 per cent in the last six years. As the share of household indebtedness increases, stress in this sector – triggered by a rapid increase in interest rates, an increase in unemployment, a high level of inflation, and a sharp decline in housing prices, or combination thereof – could have a significant impact on the banking sector.

Therefore, it is important to continuously assess (i) banking sector's exposure to the household sector, and (ii) the household sector's financial resilience, which play a critical role in the financial system where mortgages dominate financial institutions' balance sheet. Stress testing is a useful tool to assess the resilience of the financial system to various shocks, including those that result in more borrowers being unable to repay their debts (i.e., adverse economic shocks to households). While the Bank of Mongolia and the IMF have conducted some formal stress tests of the Mongolian banking sector, a stress-testing framework for the Mongolian financial system has not systematically developed at the authorities, which have the mandate to ensure the financial stability.

This paper aims to develop a simulation-based household stress-testing model that assesses the financial resilience of households to macroeconomic shocks using data from the Household Socio-Economic Survey (HSES) of Mongolia. The model is characterized by specific features of Mongolian households and the banking sector, and fits with major components of the HSES data. Though it is different from the formal stress testing, the model is able to (i) quantify household financial resilience and exposure to shocks, and (ii) estimate the banking sector's exposure to households that are more likely to default. Comparing to the aggregate data (i.e., the household debt-to-income ratio), household surveys provide more insights into households' ability to pay as they contain information on the distributions of household debt, assets, and income. As shown by Bilston et al. (2015), aggregate measures of household indebtedness can be misleading indicators of the household sector's financial fragility. For instance, it is possible that even with rising levels of household indebtedness in aggregate, the distribution of household debt remained concentrated among households that are well placed to service. In addition, macro data are of limited use in differentiating between households that hold debt and those that do not hold and do not include information about which households hold the risky forms of debt and which households hold enough assets to cover their assets.

As far as we are aware, this paper is a first attempt to test Mongolian households' financial resilience using the micro-simulation model, which has become an increasingly popular tool for stress testing household credit risk and assessing financial stability risks resulting from household debt. Thus, it contributes to the development of a complete stress-testing framework for the Mongolian financial system as the stress testing of household loan portfolio is one important component of the framework.

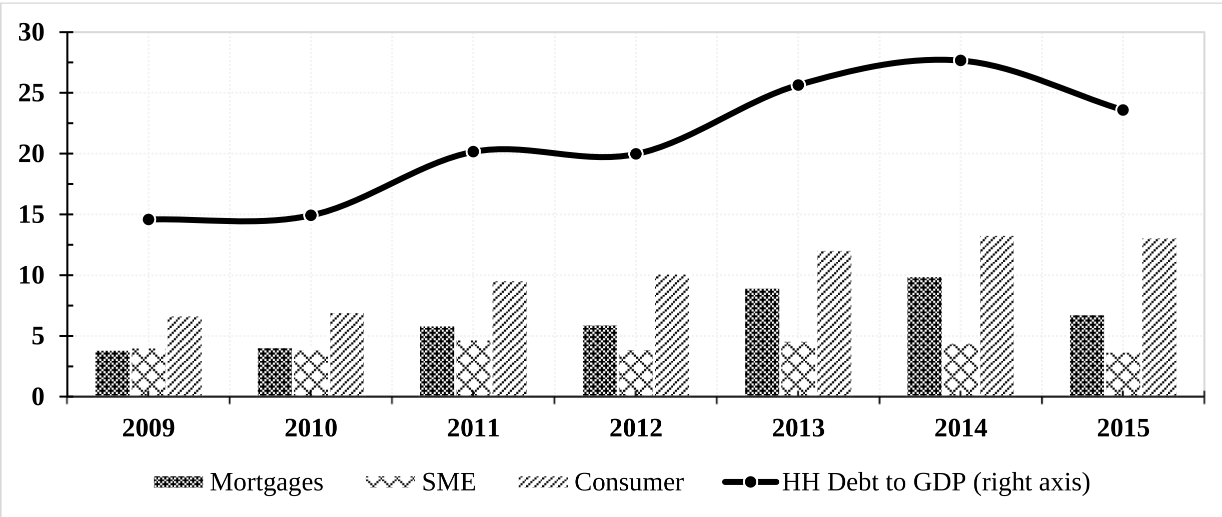
The stress-testing model is based on 'financial margin approach'[2], where each household is assigned a financial margin, which is usually the difference between each household's income and estimated minimum expenses. The model also shares many features with the existing models for several countries (e.g., Karasulu (2008) for the South Korea, Albacete and Fessler (2010) for Austria, Sugawara and Zalduendo (2011) for Croatia, Djoudad (2012) for Canada, Galuščák et al. (2014) for Czech Republic and Bilston and Rodgers (2013) and Bilston et al. (2015) for Australia).

The remainder of this paper is structured as follows. Section 2 presents a household and financial sector nexus in Mongolia. Section 3 describes our stress-testing model and Section 4 discusses pre-stress and post-stress test results. Section 5 presents limitations of, and potential improvements to the model and to future HSES surveys. Section 6 concludes.

2. Model

The Mongolian household sector's aggregate level of indebtedness has increased from 14 per cent to 25 per cent in terms of GDP between 2009 and 2015. The ratio of household financial debt to disposable income has significantly expanded and reached to 28.2 per cent at the highest in 2014. This is closer to the average of the new EU member countries and higher than the average of middle-income CIS (Tiongson et al., 2012). More than one third of the Mongolian household debt consists of mortgage loans. The ratio of mortgage loan to disposable income reached to the peak of 10.1 per cent in 2014 from 4.4 per cent in 2009. During the same period, the consumer loan-to-disposable income ratio has almost doubled while the ratio of small and medium enterprise loans remains stable around 4.0 per cent (Figure 2.1).

FIGURE 2.1 HOUSEHOLD DEBT TO DISPOSABLE INCOME RATIO BY TYPES

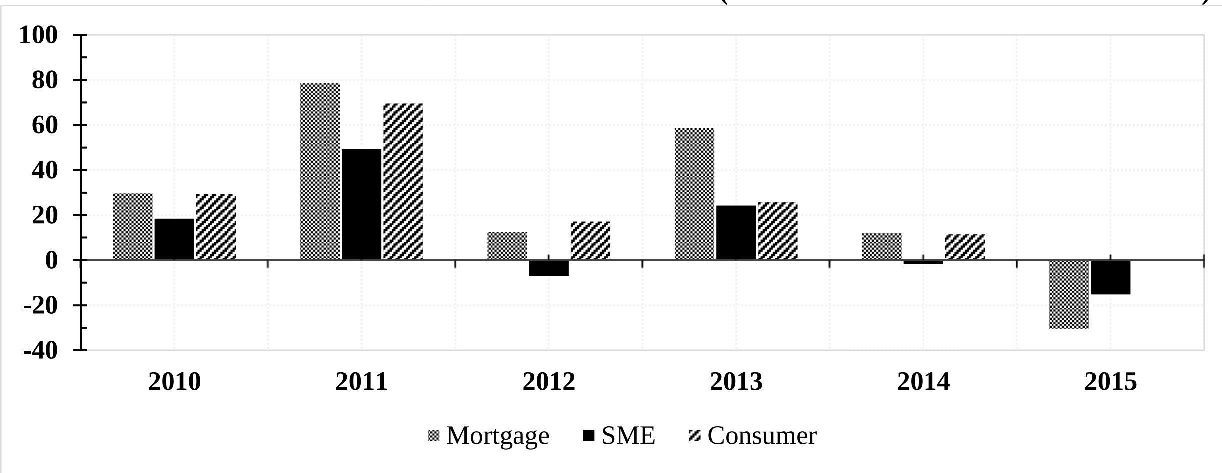


Source: BOM, Monthly Statistical Bulletin, March 2016 NSO, Statistical Yearbook, 2015

The average annual percentage change of mortgage loan was 38.7 per cent between 2010 and 2014 except the negative growth of -30.9 per cent in 2015. The mortgage loan growth has been higher than the growth of the SME (Figure 2.2). The average growth rate of household debt has significantly surpassed the GDP growth over last years.

[2] Financial margin type approaches are also known as the household budget constraint method, financial surplus method or the residual income approach in the literature.

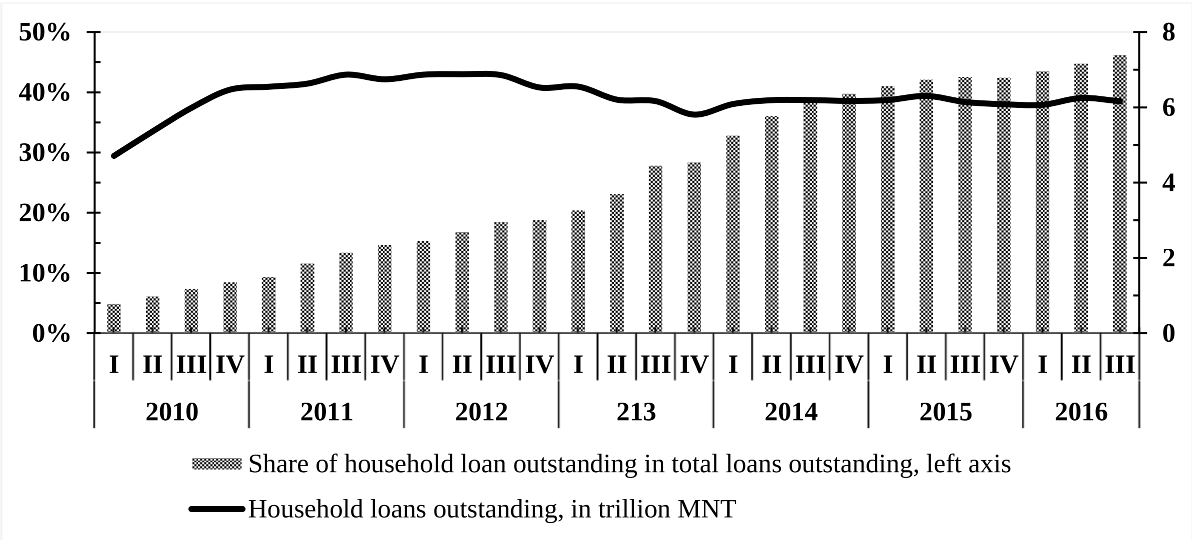
FIGURE 2.2 HOUSEHOLD DEBT (YEAR-ON-YEAR PER CENT CHANGE)



Source: BOM, Monthly Statistical Bulletin, March 2016

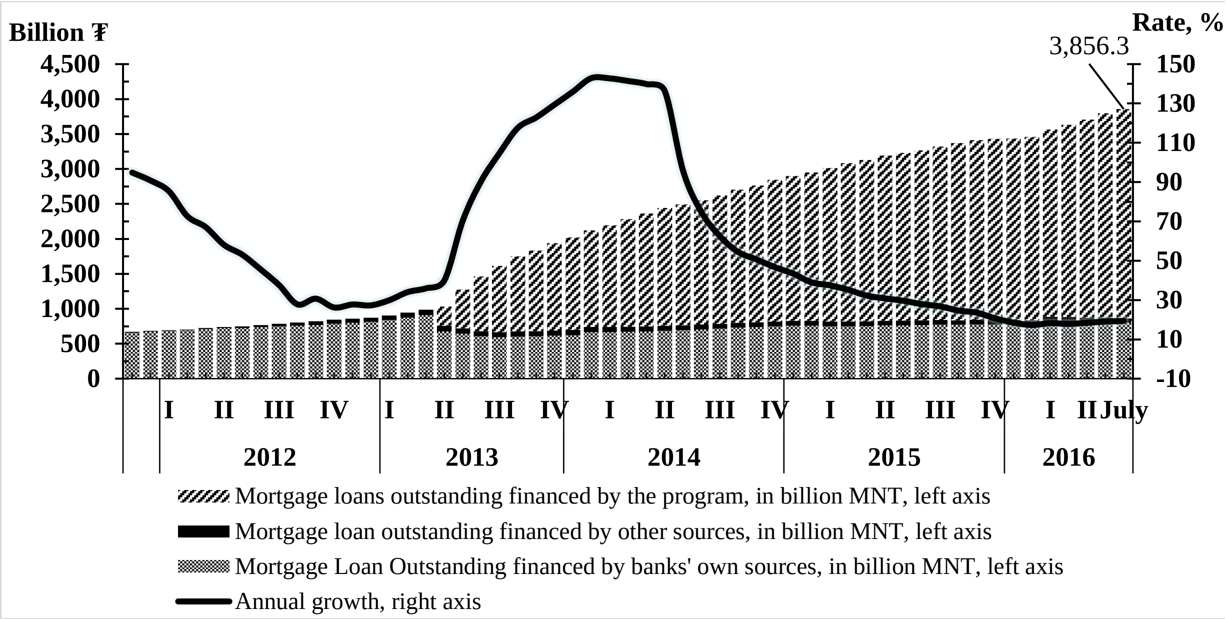
The rapid increase in household sector indebtedness raises concerns about mortgage loan risk and the financial stability. The household sector loans outstanding accounts for 40 per cent of total loans outstanding in the banking sector (Figure 2.3). As a result of the government program on establishing a sustainable mortgage financing, the households' mortgage debt outstanding has tripled to 3.4 trillion MNT, accounting for half of the total household loans outstanding (Figure 2.4).

FIGURE 2.3 HOUSEHOLD LOANS OUTSTANDING



Source: BOM, Monthly Statistical Bulletin, March 2016

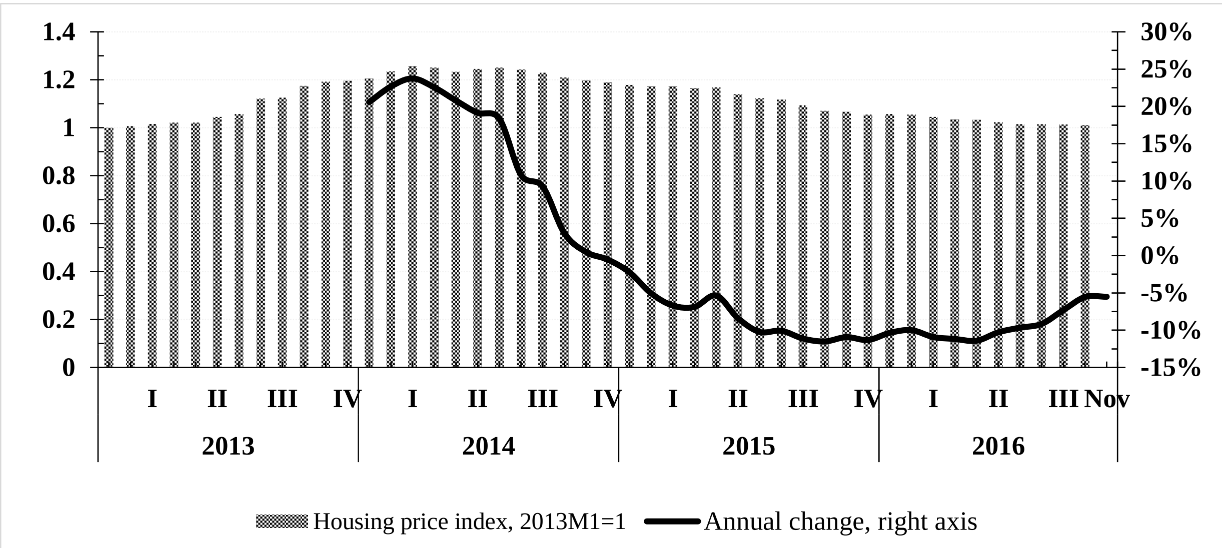
FIGURE 2.4 MORTGAGE LOANS OUTSTANDING



Source: BOM, Report on banks' mortgage loan

Mongolia has experienced the boom-bust cycle in the housing market. The average annual growth of housing prices was 15.6 per cent till November 2014 and since then a continuous price decline has been observed in the housing market. The housing price index dropped by 8.7 percent a year on average for last two years (Figure 2.5).

FIGURE 2.5 HOUSING PRICE INDEXES (2013/01=100)

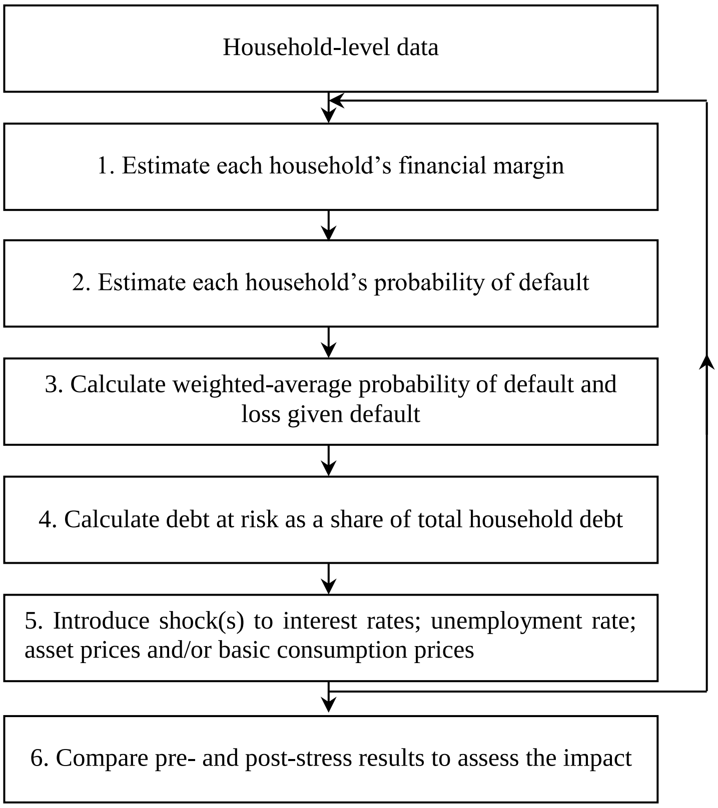


Source: BOM, Monthly Statistical Bulletin, March 2016

3. Data

The model is based on the financial margin approach employed by Albacete and Fessler (2010) and closely follows models formulated by Bilston and Rodgers (2013) and Bilston et al. (2015). In this approach, households with negative financial margins are assumed to default their debts. The steps involved in the model are shown in Figure 3.1.

FIGURES 3.1 SCHEMATIC REPRESENTATION OF THE MODEL



Source: Authors modified the scheme shown by Bilston and Rodgers (2013).

The household level data is used to estimate loss given default and 'debt at risk' (or expected loan losses) when combined with information on which households are assumed to default. In the stress testing, shocks to macroeconomic variables, such as asset prices, exchange rates, interest rates and the unemployment rate, have been considered. The impacts of these shocks can be estimated by comparing pre- and post-shock default rates and loan losses. The steps involved in the model are detailed below.

3.1. Household-level data

The Mongolian stress-testing model uses the HSES data, which is a nationally representative household-based longitudinal study collected annually since 2007/2008[3]. The National Statistical Office reports the data annually. The survey contains information about household and individual characteristics, consumptions, financial conditions, employment, and wellbeing.

In this paper, we use the HSES data in 2012 and 2014. The sample sizes are 12811 and 16714 households in 2012 and 2014, respectively. The households are sampled from 21 provinces and Ulaanbaatar and therefore nationally representative. The Table 3.1 shows the statistics of household characteristics, total income and expenditures from HSES 2014. Data on individual characteristics are used to estimate probabilities of unemployment, and the model of unemployment is based on a sample of more than 40 thousand individuals[4].

[3] The first HSES survey was conducted in 2002/2003, however this is not comparable to others as the questionnaire and methodology was different.
[4] In 2014, a total number of individuals in the HSES were 58852, out of which 40723 were aged 16 and over. These individuals are used in the simulation.

TABLE 3.1 SUMMARY OF STATISTICS

Variables	Mean	Std. Dev.	Min	Max	Obs.
Household characteristics					
Household size	3.5	1.6	1	13	16,174
HH head age	45.7	14.2	16	107	16,174
Number of children	1.1	1.2	0	7	16,174
Household Income and Expenditure (in million MNT)					
Total Income	11.7	9.9	0.01	183.0	16,165
Wage	9.3	6.8	0.05	94.0	9,253
Remittance	2.2	3.9	0.01	93.0	3,182
Other[5]	0.2	2.1	0.02	51.4	14,272
Total Expenditure	5.7	2.9	0.39	103.0	16,174
Food Expenditure	3.3	1.6	0.09	25.0	16,174
Non-food Expenditure[6]	2.4	1.9	0.02	99.5	16,174

Source: NSO, HSES 2014

3.2. Estimating households' financial margin

The first step is to establish a pre-stress baseline. To this end, the financial margin, FM_i, of a household i is estimated as

$$\boldsymbol{FM_i = Y_i - BC_i - DS_i - R_i} \tag{3.1}$$

where $Y_i = I_i - T_i$ is the i-th household's disposable income, I_i is the household's total income before tax, T_i is tax amount paid by the household, BC_i is basic consumption expenditure, DS_i is minimum debt servicing cost (if any) and R_i is rental payment (if any). All measures are in annual basis or annualized before inclusion (i.e., monthly data is multiplied by 12 to obtain annual figure). While Y_i and R_i are reported in the HSES survey, BC_i is not directly available from the survey. In a scenario of financial stress, basic consumption is of greater relevance than actual consumption as households can reduce discretionary spending to meet their debt obligations.

The basic living expenses is approximated by sum of expenses on food ($C_{F,i}$), transportation ($C_{T,i}$), energy ($C_{E,i}$), health ($C_{H,i}$) and clothes ($C_{C,i}$):

$$\boldsymbol{BC_i = C_{F,i} + C_{T,i} + C_{E,i} + C_{H,i} + C_{C,i}} \tag{3.2}$$

The HSES survey only contains information about annual payments on the existing loans. Therefore, minimum debt servicing costs are estimated as:

$$\boldsymbol{DS_i = PM_i + PC_i + PO_i} \tag{3.3}$$

where PM_i is the annual mortgage payment, PC_i and PO_i are the annual payments on consumer debt (i.e., sum of salary loan, pension loan, household consumption loan and herder loan) and other debts (i.e., sum of business loan, leasing loan, car loan and other loan), respectively.

To estimate household's total debt, we need households' outstanding loan balances. However, the HSES survey does not include information about households' outstanding loan balances. Fortunately, the HSES survey consists of the original loan balance (J_{0i}) if the loan is taken within last 12 months. For the loans taken within last 12 months, the end-of-period

[5] Other income consists of all types of household production incomes and welfare payments.

[6] Non-Food expenditure consists of transportation, clothing, taxes paid, energy, and health expenditures as essentials.

outstanding loan balances at the period, $J_{12,i}$, are calculated using the following simple formula[7]:

$$\boldsymbol{J_{12,i}} = \frac{\left((1+r_J)^{T_{Ji}}-(1+r_J)^{0+12}\right)}{\left((1+r_J)^{T_{Ji}}-1\right)} \boldsymbol{J_{0i}}, \boldsymbol{for\ J} \in \{\boldsymbol{M}, \boldsymbol{C}, \boldsymbol{O}\} \tag{3.4}$$

where M, P and O respectively represent mortgage, consumer and other loans, r_J is the (monthly) interest rate for J-type loan at the period, J_{0i} is original balance for J-type loan of the household, and T_{Ji} is the initial loan term (in months) for J-type loan of the household calculated as follows:

$$\boldsymbol{T_{Ji}} = \frac{ln(pj_i/(pj_i - r_J J_{0i}))}{ln(1+r_J)} \tag{3.5}$$

where $pj_i = PJ_i/12$ is the monthly payment for the J-type loan (i.e., from the survey, we have annual payment number for J-type loan, thus to obtain monthly payment we divide PJ_i by 12). If T_{Ji} cannot be calculated due to the inconsistency among the answers of the household (i.e., the calculated T_{Ji} is negative), then the outstanding loan balance of the household (J_i) is taken as the outstanding loans, which are not taken within last 12 months.

For the loans, which are not taken within last 12 months, the outstanding of loan, having k years old (in months) at the period, $J_{k,i}$, are approximated as follows (if the interest rate is constant):

$$\boldsymbol{J_{k,i}} = \frac{\left((1+r_J)^{T_J}-(1+r_J)^{k_J+12}\right)}{\left((1+r_J)^{T_J}-1\right)} \boldsymbol{J^e_{0i}},, \boldsymbol{for\ J} \in \{\boldsymbol{M}, \boldsymbol{C}, \boldsymbol{O}\} \tag{3.6}$$

where T_J is the initial loan term (in months) for the J-type loan, k_J is the old (in months) of the J-type loan, and J^e_{0i} is the estimated original balance for J-type loan calculated from the monthly mortgage payments using a credit-foncier model as follows:

$$\boldsymbol{J^e_{0i}} = \frac{\left((1+r_J)^{T_J}-1\right)}{r_J(1+r_J)^{T_J}} \boldsymbol{pj_i} \tag{3.7}$$

If $J_{12,i}$ and $J_{k,i}$ give the negative values due to the inconsistency among the answers of the household, the household's original loan balance are used for the outstanding loan balance.

Once we obtained the outstanding balance for the J-type loan, then each household's total debt, D_i at the period is estimated as

$$\boldsymbol{D_i} = \boldsymbol{M_{k,i}} + \boldsymbol{C_{0i}} + \boldsymbol{O_{0i}} \tag{3.8}$$

3.3. Calculating probabilities of default, exposure at default and loss given default

The percentage of vulnerable households is the key measure to monitor the resilience of households under different shocks. Therefore, in the second step, we use the financial margin to calculate each household's probability of default (PD_i) as follows:

$$\boldsymbol{PD_i} = \begin{cases} \mathbf{1} & \boldsymbol{if\ FM_i} < \mathbf{0} \\ \mathbf{0} & \boldsymbol{if\ FM_i} \geq \mathbf{0} \end{cases} \tag{3.9}$$

In the model, households having a negative financial margin (i.e., not able to cover all their spending from income) are in financial stress[8]. Thus, households with $PD = 1$ are assumed to

[7] The calculation is based on the given information (i.e., monthly payment, interest rate and the original loan balance) and a credit-foncier model (i.e., a standard financial formula to calculate mortgage payments on amortizing loans).

default with certainty. This is a simplification since some households could sell liquid assets or property to avoid default. Relaxation of the assumption is discussed and carried out by Ampudia et al. (2014). We leave this exercise for future as there is no reliable data on the household liquid asset at the currant stage.

However, the measure about vulnerable households does not provide sufficient information to monitor possible bank losses. To measure the losses under different stress scenarios, we need to take into account the share of total debt held by vulnerable households as well as these households' assets. In the third step, we calculate the household sector's weighted average probability of default (WPD), measuring the percentage share of total debt held by vulnerable households and loss given default. WPD is calculated as

$$\boldsymbol{WPD = \frac{\sum_i^N PD_i D_i}{\sum_i^N D_i}} \tag{3.10}$$

where N is the total number of households.

The weighted average loss given default as a percentage of household debt in default (LGD)[9] is defined as follows:

$$\boldsymbol{LGD = \frac{\sum_i^N PD_i L_i}{\sum_i^N PD_i D_i}} \tag{3.11}$$

where $L_i = max(D_i - W_i, 0)$ is the value that is lost as a result of a household defaulting, and W_i is the value of a household's 'eligible' collateral, which is the collateral that lenders would be able to make a claim on in the event of default. In the model, we assume that eligible collateral consists of housing assets only.

In step four, the WPD and LGD are combined to estimate the weighted average debt at risk as a share of total household debt (DAR), expected household loan losses flowing through to lenders:

$$\boldsymbol{DAR = WPD \times LGD = \frac{\sum_i^N PD_i L_i}{\sum_i^N D_i} \times 100} \tag{3.12}$$

Once the pre-stress results are established, macroeconomic shocks are applied separately or in combination to obtain post-stress results. The difference between the pre-stress and post-stress results quantifies the impact of the shock in the model. The process is repeated for 2012 and 2014.

4. Calibration and Results

4.1. Calibration

A small number of parameters in the model are calibrated based on the statistics of the Mongolian banking sector. As we use the HSES for 2014, the annual mortgage interest rate is calibrated as 8.0%, which is the fixed rate set in July 2013 under the government program on establishing sustainable mortgage financing. The annual interest rates for consumer (r_c) and other (r_o) loans are respectively calibrated as 19.0%, which is the average lending rate for 2014. The initial mortgage loan term, T_M, is calibrated as 16 years (192 months), the weighted mortgage loan term calculated using the BOM mortgage loan report for February 2016. This calibration is also consistent with the sample average estimation of the initial mortgage loan term, T_{Mi}, calculated from the HSES for 2014. The average age of the mortgage loan, k_M, is

[8] It is important to note that we only consider that households are in distress if they are unable to pay its debts. Given the available data, we cannot consider households that are able, but unwilling to service their debt. Issues such as strategic defaults are beyond the scope of this paper.

[9] It is the amount that lender are unable to recover on defaulted loans.

calibrated as 3.5 years (42 months), approximated using the mortgage loan outstanding and the starting year of mortgage loan (i.e., 2003). The initial loan term for consumer (T_C) and other (T_O) loans are respectively calibrated as 45 months and 50 months, which are the average of the sample average estimation of the initial loan terms, T_{Ci} and T_{Oi}, calculated from the HSES for 2014. The average age for consumer (k_C) and other (k_O) loans are calibrated as 9 months, approximated as 25% (~ 3.5/16 for the mortgage loan) of the maximum consumer & business loan term (36 months). The descriptive analysis of the data can be found in the Appendix.

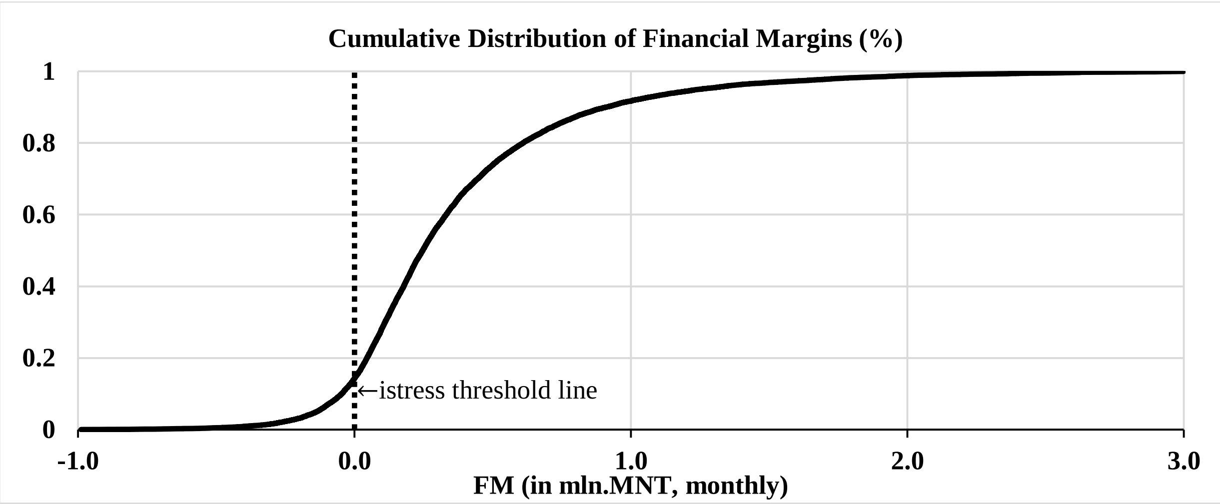
4.2. Pre-stress results

Prior to applying shocks, we review the pre-stress results and compare our results with those of other studies. The models used in both pre-stress and post-stress scenarios are programmed in Stata software.

4.2.1. Financial margins

W Cumulative distribution function of the household's financial margin is shown in the Figure 4.1. Households having the financial margin ranged [-0.5, 0.5] million MNT per months account for about 80% of total households.

FIGURE 4.1 FINANCIAL MARGIN DISTRIBUTION FUNCTION



Source: HSES 2014, Authors' calculation
Note: Only includes households with debt. Outliers excluded[10].

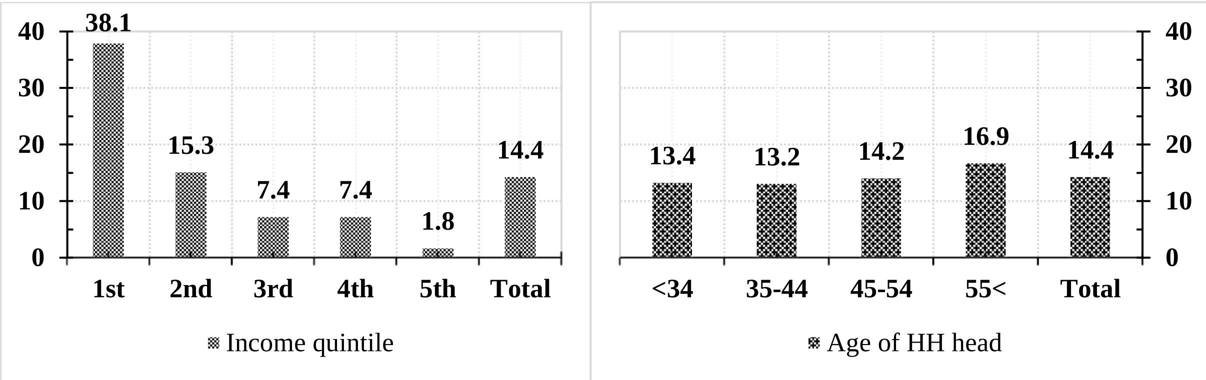
According to the model, the share of households with negative financial margins (i.e., below the threshold line) was 14.4 per cent in 2014[11]. The estimate is comparable with other countries' results. For instance, Herrala and Kauko (2007) estimate 13-19 per cent for Finland, Burke et al. (2011) at least 14 per cent for Australia, Andersen et al. (2008) 19 per cent for Norway, and Albacete and Fessler (2010) 9.2-16.5 for Austria. However, it is important to note that the estimate is sensitive to the definition of basic consumption expenditures[12]. The rest of the analysis in this section is based on the data of indebted households those who have negative financial margins.

As found by the other literature, low-income households are more likely to have negative financial margins than higher-income households. In contrast to results of the other countries,

[10] Out of 16166 households, the number of households whose financial margin is less than -1000000 and greater than 3000000 are 57 (0.35%) and 221 (1.37%), respectively.
[11] In 2012, 22.1 per cent of households had negative financial margins.
[12] The estimate, for example, is 8.3 per cent when cloth expenditures are excluded. However, in this study, we include cloth expenditures as a part of essential expenditure. For further information on general characteristics of the data, please refer to HSES report.

households with older heads are more likely to have negative financial margins than households with younger heads (Figure 4.2). The data shows that 13.4 per cent of households with a household head aged less than 34 have negative financial margins while that is 16.9 if household head's age is 55 and over. This may imply that younger households in Mongolia have less ability or appetite to borrow compared to the other countries (i.e., Austria and Australia).

FIGURE 4.2. PRE-STRESS: HOUSEHOLD WITH NEGATIVE FINANCIAL MARGINSHARE OF HOUSEHOLDS BY CHARACTERISTICS

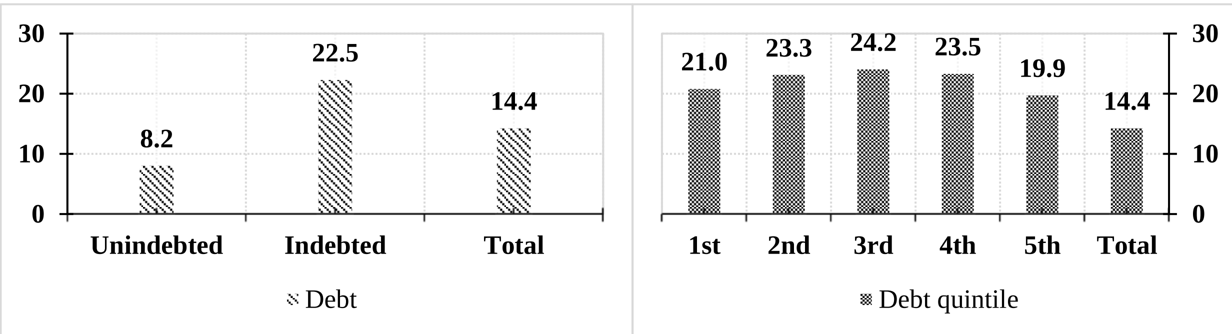


Source: HSES 2014, Authors' calculation

Indebted households are more likely to have negative financial margins than unindebted households. Interestingly, for the first three debt quantiles, the share of households with a negative financial margin tends to increase as debt increases. The share decreases for the highest two debt quintiles (Figure 4.3). In addition, regardless of the debt quintile, the share of indebted households is higher than the share of the whole households. These results suggest that indebtedness is highly correlated with financial stress in Mongolia. Moreover, this finding may indicate that the assessment of loan applications is less effective as lenders are able to predict whether potential borrowers will be able to comfortably payback the loan given their income and other expenses.

It must be noted that households with negative financial margins in the model will not necessarily default in reality as households often have assets that they can draw on, so they may be in sound financial position instead of having a negative financial margin. For example, 30 per cent of households with negative financial margins have assets – defined here as housing assets – to avoid default.

FIGURE 4.3. PRE-STRESS: HOUSEHOLDS WITH NEGATIVE FINANCIALMARGINS SHARE OF HOUSEHOLDS BY CHARACTERISTIC



Source: HSES 2014, Authors' calculation

4.2.2. Debt at risk

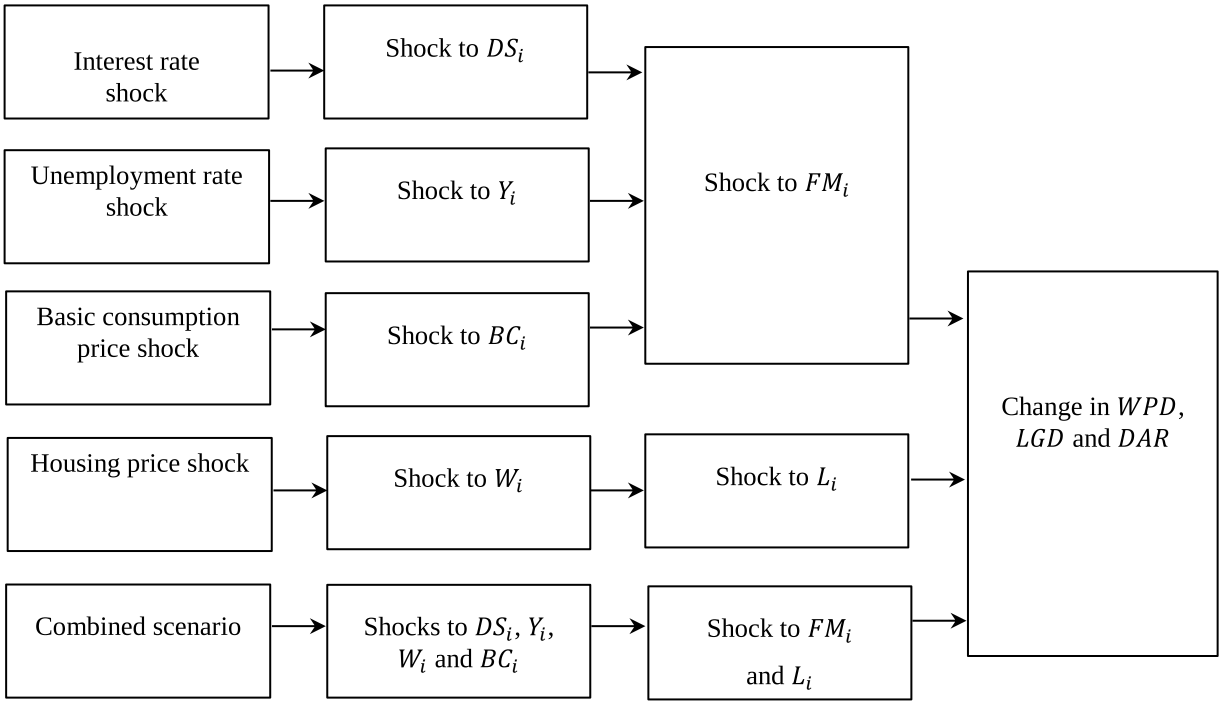
As discussed in equations (11) and (12), DAR depends on the collateral that is assumed to be recoverable by the lender in the event of default. In this paper, it is assumed that this collateral consists of housing assets (i.e., apartment and house) only. According to the model, pre-stress DAR is 7.2 per cent in 2014[13]. This estimate is quite high compared to the other literature. For example, Bilston et al. (2015) estimate 1.5 per cent in 2010 for Australia, and this is 2.1-4.1 for Austria by Albecete and Fessler (2010). Therefore, lender's exposure to households with negative financial margins appears significantly large in Mongolia.

The high estimate of DAR is also broadly consistent with actual observations. For example, the interest rate on banks' household loans except the mortgage loan has been high (more than 18 per cent per annum) because of the high non-performance loan ratio.

4.3. Stress-testing scenarios

To assess the impact of macroeconomic shocks on the financial resilience of households, stress-testing is conducted using different types of scenarios shown in Figure 4.4. First, the effects of shocks to interest rates, the unemployment rate, basic consumption price and housing price are assessed individually. Then, we apply the above shocks in combination to examine household resilience. In this section, we explain how each of these shocks operates and assess the effect of different scenarios on household credit risk in the model.

FIGURE 4.4. OUTLINE OF HOUSEHOLD STRESS-TESTING IN THE MODEL[14]



Source: Authors modify the scheme shown by HIaváč (2014) and Bank of Lithuania (2015).

4.3.1. Increase in interest rate

A household's debt service consists of amortization and interest payments. The interest payments are the part affected by a rise in interest rate[15]. The simulation of the interest rate shock (i.e., an increase in r_J) is conducted using the following formulas:

[13] DAR is 2 percentage point lower when collateral is defined more broadly as garage, ger and summer house in addition to apartment and house.

[14] Change in the exchange rate is a shock to the households' the basic consumption, MC_i through changes in consumption prices and debt service, BC_i, of the households with foreign currency loans. Though there is a possibility that a change in exchange rate could be a shock to the households' income, Y_i, as wages of household members are denominated in foreign currencies. Unfortunately, we do not analyze the impact of the shock as we do not have enough information, including how many per cent of the household loan and income is in foreign currency.

For the loans taken within last 12 months:

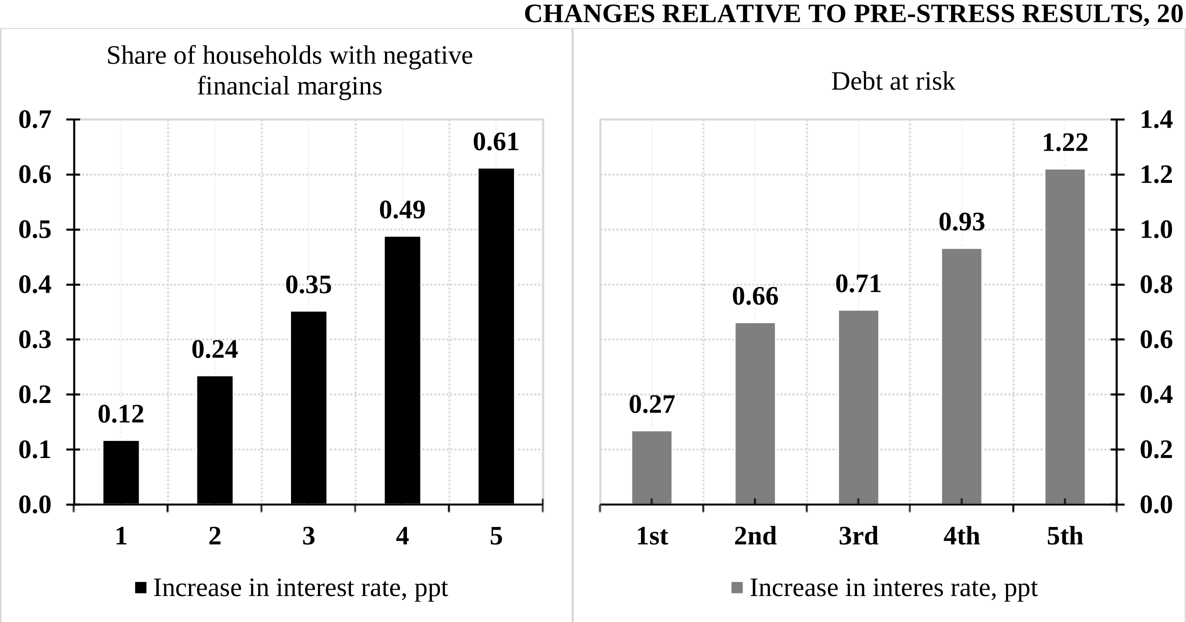
$$\boldsymbol{pj_i = \frac{r_J(1+r_J)^{T_{Ji}}}{\left((1+r_J)^{T_{Ji}}-1\right)} J_{0i}} \tag{4.1}$$

For the loans not taken within last 12 months:

$$\boldsymbol{pj_i = \frac{r_J(1+r_J)^{T_J}}{\left((1+r_J)^{T_J}-1\right)} J^{e}_{0i}} \tag{4.2}$$

Annual payment for or the J-type loan is calculated as $PJ_i = 12 \cdot pj_i$. Thus, an increase in interest rate is a shock to the households' debt service, DS_i, and lowers their financial margins. Interest rate shocks lead to an increase in the share of households with negative financial margins, and hence the share of household assumed to default. The shock is assumed to pass through in equal measure to all household loans. We increase the debt service in line with the assumed rise in the interest rate and assuming that the loan (and interest) is still repaid according to schedule (i.e., without expanding the maturity of the loan).

FIGURE 4.5 EFFECT OF INCREASE IN INTEREST RATES CHANGES RELATIVE TO PRE-STRESS RESULTS, 2014



Source: HSES 2014, Authors' calculation

An increase in interest rate leads to an increase in debt servicing costs for indebted households, lowering their financial margins. As a result, the share of households assumed to default will tend to increase.

The result indicates that a 1 percentage increase in interest rate causes the share of households with negative financial margins to increase by 0.12 percentage points and DAR to rise by 0.27 percentage points (Figure 4.5). The larger the increase in interest rate, the greater the share of households with negative financial margins. We can see a sharp rise in the DAR between 1 and 2 percentage point increases in interest rate. In other words, the DAR is relatively more responsive to the change in interest rate from 1 to 2 percentage points than further percentage point increases.

[15] In the short term, the shock affects to indebted households, which have variable interest rate. In the long run, fixed interest rate loans are also affected by such a shock owing to a renegotiation of interest rates.

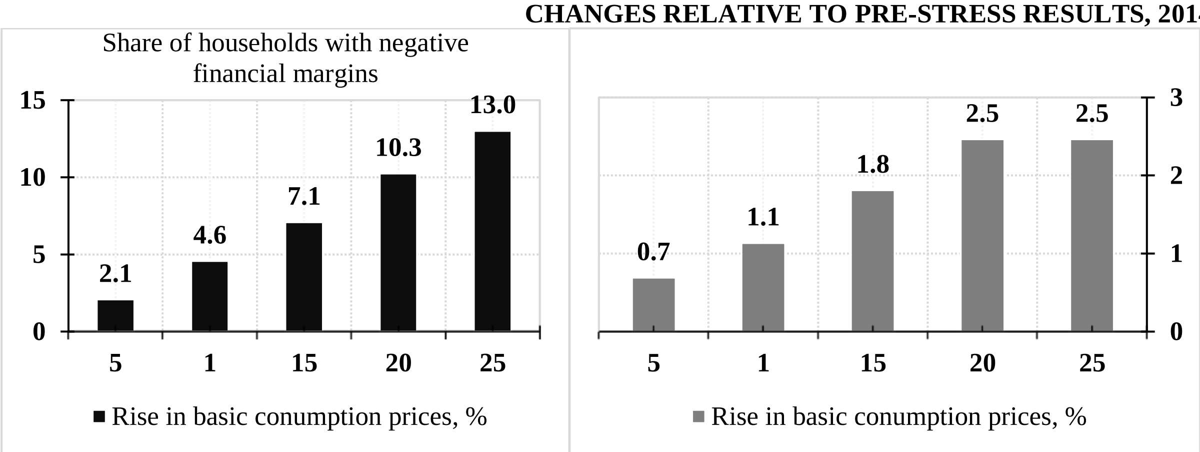
4.3.2. Changes in basic consumption prices

Changes in prices of the basic consumption basket items are shocks to households' basic consumption items, C_j, for $j = F, T, E, H, C$. The basic consumption items are assumed to be price inelastic. Though the assumption is realistic for the essential goods, this is a sort of simplification as some households could change their basic consumptions when prices the essential goods increase. For this version of the model[16], we rely on the inelastic assumption as there are no preliminary studies on the price elasticities of essential goods in the case of Mongolia. It is also important to note that this version of the model ignores the effect of inflation on the value of nominal assets and liabilities.

Thus, a rise in the price of the basic consumption item leads to an increase in BC_i, lowering the financial margins of the households.

A 5 per cent rise in prices of all basic consumption items[17] causes the share of households with negative financial margins to increase by 2.1 percentage points and DAR to increase by 0.7 percentage points (Figure 4.6). For larger rises in prices of basic consumption, the share of households with negative financial margins rises approximately linearly (i.e., increases by 2.5 percentage points for each extra 5 per cent increase in basic consumption prices), however the effect on DAR is not linear. These households whose financial margins fell to below zero after the shock tend to have debt that are well collateralized, and therefore the impact on DAR could be limited.

FIGURE 4.6 EFFECT OF RISE IN BASIS CONSUMPTION PRICES CHANGES RELATIVE TO PRE-STRESS RESULTS, 2014



Source: HSES 2014, Authors' calculation

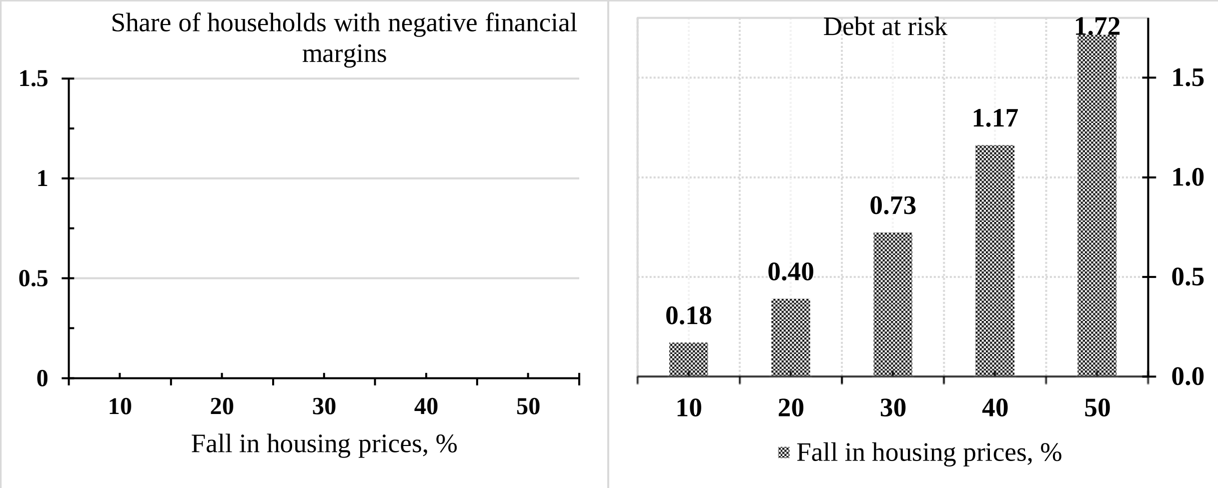
4.3.3. Changes in housing prices

Changes in housing prices are shocks to households' real estate wealth, W_i. For instance, falling housing prices increases LGD, however no effect on the share of households with negative financial margins. We assume that a given asset price shock applies equally to all households.

However, falling housing prices has no effect on the share of households with negative financial margins as we assume that housing price (i.e., value of collateral asset, W) only affects LGD through changing the loss of defaulting household (i.e, $L_i = max(D_i - W_i, 0)$). Mortgagers are the most affected by this shock. A 30 percent fall in housing prices causes DAR to increase by 0.73 percentage points. The impact is relatively small compared to results of other countries. However, the significant drop in housing price leads to higher DAR.

[16] Caluščák et al. (2014) have relaxed the assumption by using price elasticities of essential goods.
[17] Depending on the situation, it is possible to conduct stress-testing of the shock to price of the specific item. To make it simple, in the analysis, we assume same per cent price increases for all items of basic consumption.

FIGURE 4.7 EFFECT OF FALL IN HOUSING PRICESCHANGES RELATIVE TO PRE-STRESS RESULTS, 2014



Source: HSES 2014, Authors' calculation

4.3.4. Rising unemployment

When employed household member loses his or her job, this is a shock to the household's income, Y_i. For instance, a rise in the unemployment rate causes the income of individuals becoming unemployed to fall to an estimate of the unemployed benefits, lowering the financial margins of the affected households.

For the purpose of identifying unemployment shock, we divide all adults in the survey into three categories by economic activity: working, unemployed and economically inactive. People outside the labour market, such as students, women on maternity leave and people with long-term sick are assumed to remain economically inactive over the time period considered. Thus, these individuals are not included in the sample for the simulation analysis.

There are different approaches used to simulate unemployment rate shocks in the literature. Albacete and Fessler (2010) allow only homeowners (i.e., other persons in the same household do not enter in the analysis) to enter unemployment, where the probability that each homeowner becomes unemployed is estimated using a logit model. Fuenzalida and Rui-Tagle (2009) consider individuals to become unemployed with unemployment probabilities estimated using survival analysis. Bilston et al. (2015) use a logit model to estimate the probability of unemployment for each individual. However, Holló and Rapp (2007) and Sveriges Riskbank (2009) use the assumption that each individual has an equal probability of becoming unemployed.

Following Bilston et al. (2015), we use a logit model to estimate the probability of individuals becoming unemployed. As not every working person in an economy has the same probability of becoming unemployed, we need to define the probability of becoming unemployed for each working individual in our sample. We estimate the following logit model to get probabilities of unemployment for all individuals, pu_j:

$$\boldsymbol{pu_j = Pr(U_j = 1 | x_j\beta) = F(x_j\beta) = \frac{1}{1+e^{-x_j\beta}}} \quad \textbf{(4.3)}$$

where U_j is an indicator variable equal to one if individual j is unemployed and equal to zero otherwise, $\mathbf{x}_j$ is a vector of independent variables including age, age squared, gender, educational attainment (completed year 10, Diploma and University), family structure (number of children, number of adults), household income, marital status, long-term health condition, and previously unemployed for at least one year, $\boldsymbol{\beta}$ is a vector of coefficients, and $F(\cdot)$ is the cumulative distribution function of the logistic distribution. To select the independent variables, we use a general-to-specific modelling approach, removing insignificant variables to arrive at a parsimonious model. The results are shown in Table 4.1.

All remaining variables significant are significant, or for categorical variables jointly significant, at the 5 per cent level. The signs of each marginal effect are generally as expected. Man, not being married, not being in poor health, less education, being in age less than 45, being a member of large household, living in ger, being in Aimag center, or living in Eastern region increase the probability if being unemployed. Married men are more likely to be unemployed compared to married women. A man with bachelor degree or age above 45 is more likely to be unemployed to women with same characteristics.

Examining the size of each marginal effect provides us the possibility of which variables have the greatest effect on the predictor of unemployment. Using a base case, where all categorical and dummy variables are set to the sample mode and continuous variables to the sample mean, shows that many variables in the regression have sizeable effects on unemployment. For instance, living in aimag center increases the base case individual's probability of being unemployed by between 1.5 and 2.4 percentage points. Conversely, master or PhD degree education reduces the probability of unemployed by the probability of being unemployed by 10.4 percentage points.

Using the logit model, we estimate the probability of individuals becoming unemployed. This means that unemployment shocks in the model will tend to affect individuals with characteristics that have historically been associated with a greater likelihood of being unemployed. The unemployed probabilities are used to yield unemployment rate shocks. A rise in unemployment rate is simulated by increasing the constant of the model until the rate of unemployment matches the required level. The simulation of changes in unemployment assumes transitions from employment to unemployment and vice versa.

After a probability of unemployment is assigned to each individual (pu_j) using the resulting model and the existing data, we draw from a uniform distribution a random a real number, $\eta_j \in [0;1]$ for each single individual. If $pu_j \geq \eta_j$, we select the individual as unemployed. In the case of becoming unemployed, we assume that the individual's income is replaced by unemployment benefit while the income of other household members remains constant. According to the Mongolian law on distributing unemployment benefit from social insurance fund, the amount of unemployment benefit is determined by previous work income and by working years. For instance, the amount of unemployment benefit is 45%, 50%, 60% and 70% of the monthly salary for the person who has worked for less than 5 years, 5-10 years, 10-15 years, and more than 15 years, respectively.

The unemployment shock changes the household total income before tax, $I_{ub,i}$. However, we need the household disposable income, $Y_{ub,i}$ after the shock, and cannot assume that the tax amount paid by the household is same since the tax amount is changed with the income levels. Thus, $Y_{ub,i}$ is estimated as

$$\boldsymbol{Y_{ub,i} = ETR_i I_{ub,i}} \tag{4.4}$$

where $ETR_i = T_i / I_i$ is the effective tax rate.

We repeat these steps 1000 times using Monte Carlo simulation, each time calculate the vulnerability indicators, and finally take the mean of each indicator over all simulated draws.

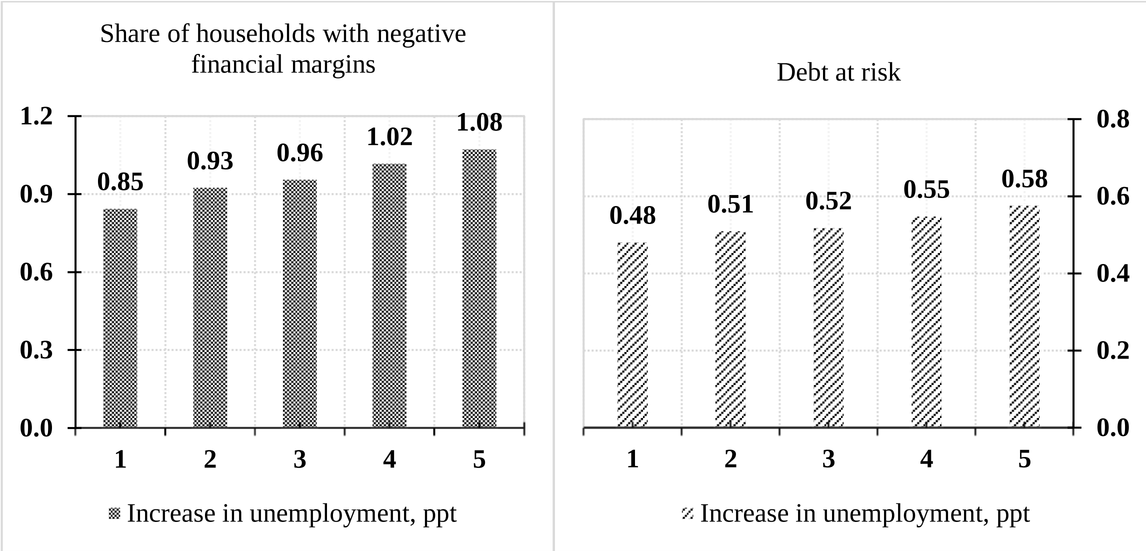
TABLE 4.1. LOGIT MODEL- UNEMPLOYMENT INDIVIDUALS IN LABOUR FORCE

Variable	Marginal effects at sample mean		
	Persons	Men	Women
Man	-0.126***		
Married	-0.211***	-0.085***	0.034***
Health condition	0.068***	0.074**	0.065*
Educational attainment			
Completed year 10/12	0.089***	0.067***	0.12***
Diploma/Certificate	0.014**	0.024***	0.007
Bachelor	-0.003	0.026**	-0.022*
Master & PhD	-0.104***	-0.078***	-0.140***
Demographic characteristics			
Age	-0.049***	-0.036***	-0.063***
Age squared	0.0007***	0.0005***	0.0009***
Age 21-24	0.062***	0.022*	0.118***
Age 25-34	0.077***	0.040**	0.122***
Age 35-44	0.028	0.058***	0.004
Age 45-54	-0.027**	0.003	-0.070***
Family structure			
Household size	0.018***	0.010***	0.027***
Single with dependent	-0.024**	-0.017	-0.006
Housing type			
Ger	0.010***	0.004	0.018**
Apartment	-0.031***	-0.025***	-0.037***
Administrative units			
UB capital city	0.012*	-0.026***	0.056***
Aimag center	0.019***	0.015**	0.024***
Rural	-0.143***	-0.098***	-0.197***
Geographical regions			
Western	-0.025***	-0.016**	-0.034***
Highlands	-0.026***	-0.018***	-0.033***
Eastern	0.004	0.014*	-0.009
Predicted probability at means	0.16	0.11	0.22
Pseudo-R^2	0.12	0.12	0.11
Number of observations	28895	14466	14429
log-likelihood	-12609.1	-5142.8	-7315.6

Notes: *, **, *** denote significance at the 10, 5 and 1 per cent levels, respectively, for the test of underlying coefficient being zero. Marginal effects calculated for dummy variables as a discrete change from 0 to 1 and for continuous variables as a one-unit change.
Source: HSES 2014, Authors' calculation

A 1 percentage point increase in unemployment rate increases the share of households with negative financial margins by 0.85 percentage points, and a 5 percentage points increase leads to increase share by 1.08 percentage points (Figure 4.8). The impact of 1 percentage point increase in unemployment rate has a 0.48 percentage point increase in DAR. The marginal impact of a change in unemployment on the share of households with negative financial margins and on debt at risk is relatively small compared to other shocks. This is because the 57 per cent of households report wage income while the remaining households depend on other types of incomes. Thus the impact on income is almost insignificant.

FIGURE 4.8 EFFECT OF RISE IN UNEMPLOYMENT CHANGES RELATIVE TO PRE-STRESS RESULTS, 2014



Source: HSES 2014, Authors' calculation

4.3.5. Combined scenarios

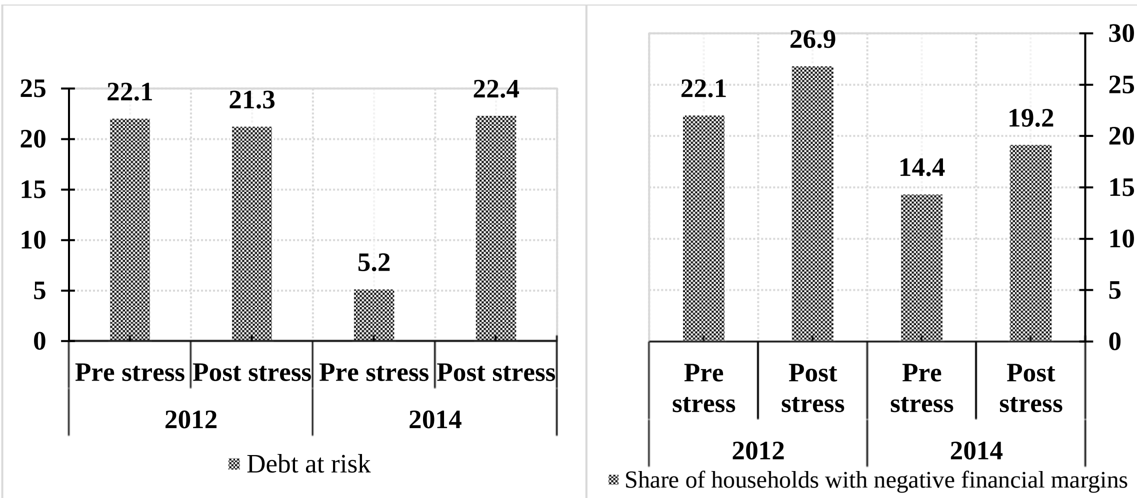
In this section, we apply shocks in combination to examine household resilience under two scenarios, labelled 'Historical' and 'Hypothetical'. The magnitudes of the shocks under each of the scenarios are shown in Table 4.2.

TABLE 4.2 SCENARIOS

	Historical	Hypothetical
Change in housing prices (per cent)	-11.5 (2014-2015)	-20.0
Change in interest rate (ppt)	2.25 (2009-2011)	4.0
Change in basic consumption prices (per cent):	11.6 (2009-2011)	10.0

The 'Historical' scenario is designed to replicate the changes in macroeconomic conditions that occurred in Mongolia during the 2009-2011 economic recessions, except the fall in housing prices. These include a significant rise in inflation, a slight increase in unemployment, and an increase in short-term interest rate. The 'Hypothetical' scenario is much more severe than the historical scenario and is calibrated taking into account for recent macroeconomic changes.

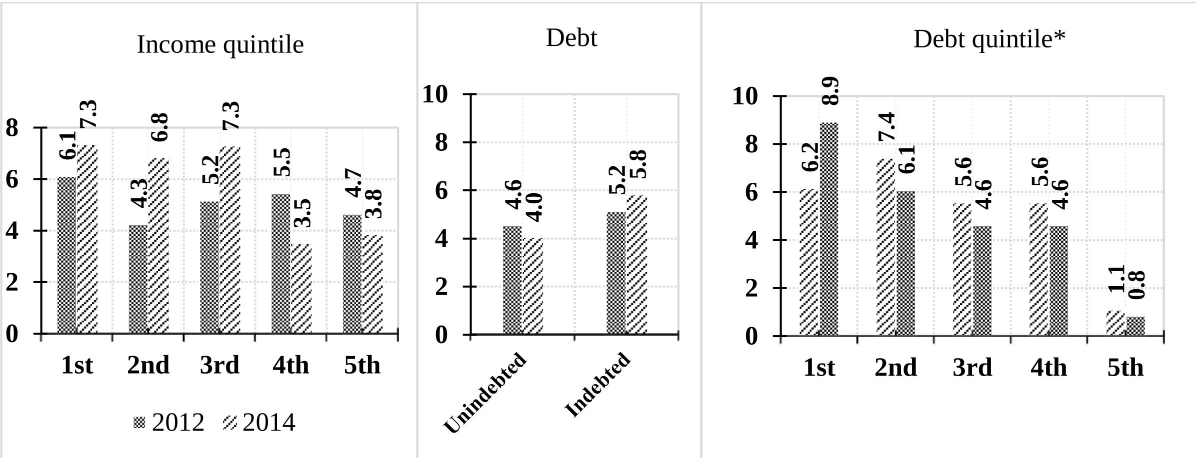
FIGURE 4.9 'HISTORICAL' SCENARIO



Source: HSES 2012 and 2014, Authors' calculation

Under the historical scenario, the share of households with negative financial margins increases by 4.79 and 4.80 percentage points in 2012 and 2014 relative to the pre-stress baseline, respectively (Figure 4.9). Comparing to other countries (i.e., Australia), the historical scenario significantly increases the share of households with negative financial margins. This is mainly due to the rise in the interest rate as the monetary policy is tightened in response to the rapid exchange rate depreciation during the economic recession (or to the high inflation which has occurred before the recession). In other countries, interest rates fall as the exchange rate risk is managed using hedging instruments, and thereby the expansionary monetary policy could offset effects of other shocks on household loan losses by reducing debt-servicing costs. Moreover, we experience a larger increase in the share of households at DAR since all our shocks have effects to decrease households' financial margins. The effect of macroeconomic shocks on DAR appears to have increased over the period 2012-2014. This suggests that household vulnerability to shocks may have risen a little.

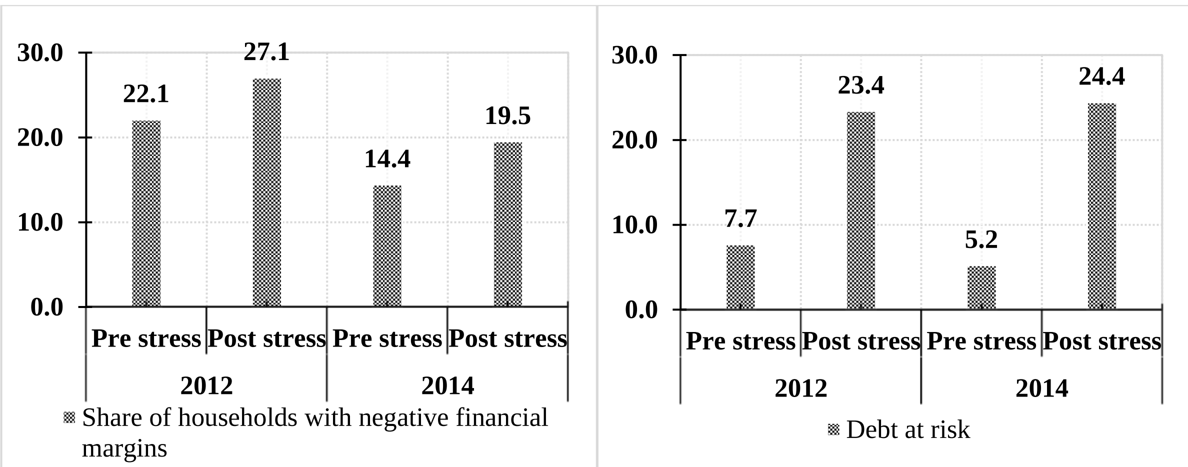
FIGURE 4.10 HISTORICAL SCENARIO-SHARE OF HOUSEHOLDS WITH NEGATIVE FINANCIAL MARGINS CHANGE RELATIVE TO PRE-STRESS



Source: HSES 2012 and 2014, Authors' calculation
Note: [a]-Indebted households only.

The rise in the share of households with negative financial margins is largest for less indebted and/or low income households.

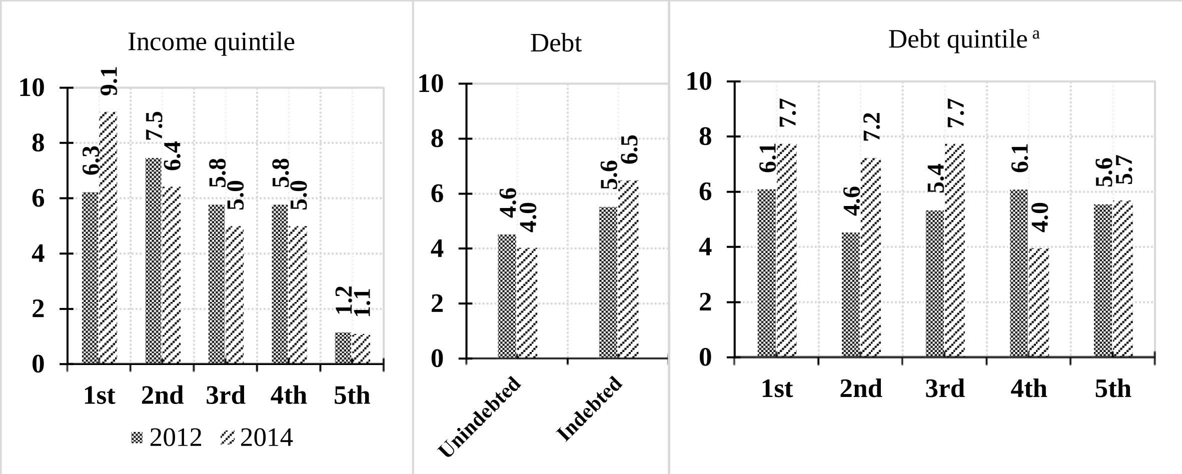
FIGURE 4.11 'HYPOTHETICAL' SCENARIO



Source: HSES 2012 and 2014, Authors' calculation

Under the 'Hypothetical' scenario, the share of households with negative financial margins rises by around 5 percentage points in each year, to total of 27.1 per cent in 2012 and 19.5 per cent in 2014 (Figure 4.11).

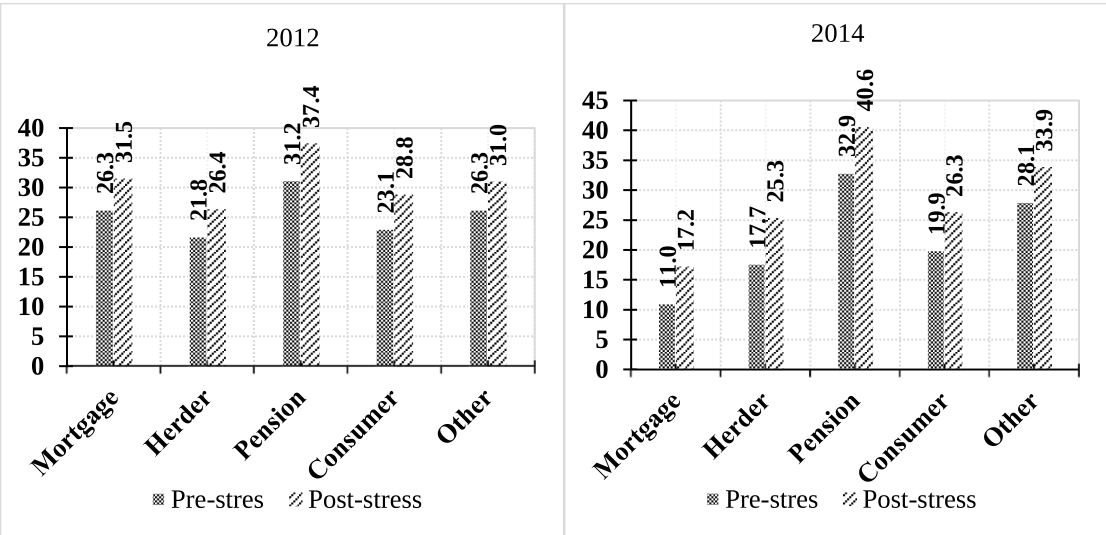
FIGURE 4.12 HYPOTHETICAL SCENARIO-SHARE OF HOUSEHOLDS WITH NEGATIVE FINANCIAL MARGINS CHANGE RELATIVE TO PRE-STRESS



Source: HSES 2012 and 2014, Authors' calculation
Note: [a]-Indebted households only.

The rise in the share of households with negative financial margins is largest for the most indebted households (Figure 4.12). The share of households with negative financial margins rises for those with low income or little debt (i.e., the first and second quintiles). The lowest (income and debt) quintile or indebted households were severely affected by the shocks in 2014 compared to 2012.

FIGURE 4.13 HYPOTHETICAL SCENARIO-SHARE OF HOUSEHOLDS WITH NEGATIVE FINANCIAL MARGINS



Source: HSES 2014, Authors' calculation

In this scenario, post-stress DAR increases relative to pre-stress DAR in each year. The effect of the shock on DAR increases over time, at 19.2 percentage points in 2014 (Figure 4.11).

Under the 'Hypothetical' scenario, the share of households with negative financial margins increases in each year. Herder households and pensioners are the most vulnerable groups to financial risks compared to other groups. The share of mortgagers with negative financial margins has declined from 2012 to 2014 as the annual mortgage interest rate has fallen to 8 per cent.

The results from the hypothetical scenario suggest that the household sector has been very vulnerable to macroeconomic shocks, and that the households that held the bulk of debt tend to face with problems to service it during macroeconomic shocks.

5. Limitations and future work

Scope of this paper includes building the household stress testing model and conducting stress-testing to study financial resilience of households and financial situations under different scenarios where different macroeconomic occur. As a preliminary step of developing the model, we need the household level data. However, Mongolian HSES survey does not include the sufficient information (i.e., household balance sheet items), which can be directly used in building the model. Thus, we made some adjustments in the survey data and used a number of assumptions.

As with all stress-testing models, the model in this paper has some limitations that are critical to its interpretation. First, the existing household surveys in Mongolia may not adequately identify households with negative financial margins as households may tend to understate their debt and income. In addition, higher-income households who possibly hold higher debts are less likely to be included in the survey, and do not disclose their financial positions. Therefore, in order to build-up the database for this type of modelling, it is better to add new questions about household balance sheets and financial statements into the existing HSES survey questionnaire. Second, as emphasized by many other papers (e.g., Bilston et al. 2015), the predictive ability of household micro-simulation has not been adequately tested. Though several countries (e.g., Austria, Australia, Canada, Croatia, Korea, and Norway) have developed similar models, none of these countries have had serious financial crisis that originated from the household sector. Thus, the stress-testing results should be frequently updated and compared with actual changes in the banking sector equity. Third, the one-period nature of the model may not be realistic in the real world as the assumptions leads to strong and instantaneous response of loan losses to macroeconomics shocks (i.e., 'jump to default' in a single period). In reality, the economic downturn involving a multi-period of shocks leads to loan losses that would be spread over time. In the future development of the model, it can be further extended to include multiple-period nature, which could potentially improve the model fit. Finally, the model needs to be further developed to assess the effect of exchange rate risk on household debt repayment as share of foreign currency loans is relatively high in Mongolia.

6. Conclusion

The indebtedness of the Mongolian household sector has increased substantially in recent years. The sharp increase in household debt has raised concerns about the sustainability of this debt and about possible risks for the banking sector. In this paper, we have developed a simulation-based model for stress testing the household sector in Mongolia, and analysed the resilience of the Mongolian household sector using micro data from HSES survey and the simulation model. This paper also provides a useful starting point for the development of a more holistic stress-testing framework for the Mongolian banking system.

The results show that the share of households with negative financial margin (i.e., income are estimated less than the minimum expenditures) declined from 22.1 per cent in 2012 to 14.4 per cent in 2014. However, the indebted share of households increased during the period. Households that were more indebted to be more likely to have negative financial margins than households that were less indebted. Households with older heads are more likely to have negative financial margins than households with younger heads.

Though the stress testing model developed in this paper relies on several assumptions, it generates plausible results in response to macroeconomic shocks. Stress testing results suggest that shocks to interest rate and basic consumption prices are particularly dangerous for financial positions of households compared to other macroeconomic shocks. A 5 per cent rise in prices of all basic consumption items leads to 0.7 percentage points increase in DAR, while a 5 percentage increase in interest rate causes DAR to rise by 1.22 percentage points[18].

Lender's exposure to households with negative financial margins appears to be large in Mongolia despite the share of households with negative financial margins falling over the 2012-2014 period. For instance, pre-stress DAR is 7.2 per cent in 2014, which is quite high compared to other countries (i.e., Australia and Austria). The increase in expected household loan losses has occurred with substantial increase in aggregate household indebtedness. Under both 'Historical' and 'Hypothetical' scenarios, the effect of macroeconomic shocks on DAR appears to have increased over the 2012-2014 period. This suggests that substantial increase in household indebtedness has increased the household sector's financial fragility. Households having pension loans are most vulnerable, while mortgagers are least vulnerable to macroeconomic shocks. In particular, pensioners are more vulnerable to inflation shocks.

In order to improve the model fit, it is better to employ the household balance sheet data rather than using proxies based on financial formulas, which are used in this paper. Therefore, some questions related to outstanding/stock data of households balance sheet (i.e., outstanding amount, maturity of each loan/deposit) should be added in the HSES survey if possible.

[18] In terms of housing prices, a 10 per cent decline leads to a 0.18 percentage point increase in DAR. A 5 percentage point increase in unemployment rate increases DAR by 0.45 percentage points.

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