

Aldashev, Alisher; Batkeyev, Birzhan

Article

Household debt, heterogeneity and financial stability: Evidence from Kazakhstan

Central Bank Review (CBR)

Provided in Cooperation with:

Central Bank of The Republic of Turkey, Ankara

Suggested Citation: Aldashev, Alisher; Batkeyev, Birzhan (2023) : Household debt, heterogeneity and financial stability: Evidence from Kazakhstan, Central Bank Review (CBR), ISSN 1303-0701, Elsevier, Amsterdam, Vol. 23, Iss. 2, pp. 1-10,
<https://doi.org/10.1016/j.cbrev.2023.100119>

This Version is available at:

<https://hdl.handle.net/10419/297959>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



Household debt, heterogeneity and financial stability: Evidence from Kazakhstan[☆]



Alisher Aldashev^{*}, Birzhan Batkeyev

International School of Economics, Kazakh-British Technical University, Almaty, 050000, Kazakhstan

ARTICLE INFO

Article history:

Received 20 October 2022
Received in revised form
20 February 2023
Accepted 8 June 2023
Available online 27 June 2023

JEL classification:

D10
D14
D31
E17

Keywords:

Stress testing
Household debt
Financial stability

ABSTRACT

Using a Monte Carlo method and quarterly data from the 2019 Household Expenditure and Income Survey, we examine the resilience of urban and rural households to various shocks, including exchange rate change, changes in asset prices, job losses, and decline in income. Based on the exposure at default (EAD) estimates, the largest impact was observed in the case of an income shock. The EAD values ranged from 0.38 to 0.43 compared to a baseline case of 0.35. The latter indicates that about one-third of the debt held by households may be problematic, especially in rural areas. The second largest impact is seen for a major currency devaluation, followed by the rise in unemployment. In addition, the breakdown of these results by income shows that households in the lower income quartiles are more vulnerable. Potential implications are discussed.

© 2023 The Authors. Published by Elsevier B.V. on behalf of Central Bank of The Republic of Turkey. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Stress tests are methods used to assess the vulnerability of portfolios to significant changes in macroeconomic conditions and are common in the financial sector. A similar approach could be used to stress-test households for their resilience during periods of economic shocks. On the micro level, stress testing analyzes the economic conditions of households when various macroeconomic

factors change: for example prices for goods and services, income, interest rates on loans, tax rates on personal income, unemployment, exchange rate, etc. Household stress testing using household sample data, as opposed to macro data, can take into account household heterogeneity and better show the mechanisms of probable bankruptcy at the micro level. This usually helps to cluster households according to their degree of vulnerability. The main purpose of the paper is to study the impact of macroeconomic shocks on the welfare of urban and rural households and their ability to meet their debt obligations.

Using the Monte Carlo method, we explore the resilience of households to shocks using the household district survey of Kazakhstan for 2019. Specifically, we analyze four stress scenarios that are common to resource-rich developing countries: exchange rate changes, rising unemployment, asset price changes, and falling incomes, as well as the combination of these shocks. Specifically, for exchange rate shock, we considered two cases of 10% and 50% currency devaluations. For the rise in unemployment, we considered the scenario of an increase in unemployment by 1, 2, and 3 percentage points. With regard to changes in asset prices, we considered the case when asset prices fall by 10, 20, and 30 percent. For income shocks, we analyze the cases where 20 percent of households lose 30, 40, and 50 percent of their income. For

[☆] This work has received financial support from the National Bank of Kazakhstan under the "Household debt, heterogeneity and financial stability" Project #533, as of 10/12/2021. Aldashev is also grateful for the financial support from the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP14869865 "Ceremonial spending, household indebtedness and poverty"). We would like to thank experts from the National Bank of Kazakhstan for helpful discussions and comments on the earlier version of this paper, two anonymous referees and also Nazym Nurkenova and Amina Karibay for excellent research assistance. The views expressed in this article are those of the authors and do not necessarily represent the position of the National Bank of Kazakhstan. Any errors and omissions are the responsibility of the authors.

^{*} Corresponding author.

E-mail addresses: a.aldashev@kbtu.kz (A. Aldashev), b.batkeyev@ise.ac (B. Batkeyev).

Peer review under responsibility of the Central Bank of the Republic of Turkey.

combined scenarios, we consider: (i) rising unemployment and devaluation shock, and (ii) falling incomes and devaluation.

Excluding the combined scenarios, out of these shocks, based on the exposure at default (EAD) estimates, the largest impact is observed for loss of income. The EAD values from this shock range from 0.38 to 0.43 depending on the magnitude of the shock compared to a baseline case of 0.35. For rural households, the range is from 0.47 to 0.51 compared to the baseline of 0.44, whereas for urban it is from 0.31 to 0.37 compared to baseline of 0.29. The overall baseline case indicates that on average about a third of the debt held by households may be problematic with 29 percent for urban and 44 percent for rural households. Hence, the income shock represents, up to an 8 percentage points increase for EAD estimates. Moreover, the results by income quartiles show that the highest effect comes from the households in the upper quartiles.

The second largest impact is seen for a major currency devaluation, followed by the rise in unemployment. A relatively small devaluation of 10% leads to an EAD increase of 3 percentage points from the base case, with 2 and 4 percentage points increase for urban and rural households, respectively. The large currency devaluation of 50% however, leads to an EAD increase of 7 percentage points with 6 and 8 percentage points increase for urban and rural households, respectively. On the other hand, the rising unemployment gives rise to EAD estimates of about 1 percentage point from the base case.

As far as combined scenarios, the biggest effect is seen in relation to income shock and devaluation. The EAD rates go up to 59 percent which illustrate a significant increase from the base case. On the other hand, the Loss Given Default (LGD) in this case reaches 5 percent, but still is generally low. This means that most of the debt is potentially collateralized by household assets. In the base case, LGD is approximately 3% for rural areas and 4% for urban areas. Therefore, even in the event of extremely negative macroeconomic shocks, only a small part of the debt is absolutely irrecoverable, that is, not secured by real estate.

2. Literature review

Stress testing of households is an important tool for macroprudential policies that are mostly carried out by the central banks of different countries. For example, [Johansson and Persson \(2007\)](#) for the Central Bank of Sweden; [Albacete and Fessler \(2010\)](#) for the Austrian National Bank; [Giordana and Ziegelmeier \(2017\)](#) for the Central Bank of Luxembourg; and also by the World Bank, [Tiongson et al. \(2010\)](#).

From developed countries, [Albacete and Fessler \(2010\)](#) used interest rate, unemployment, asset price/value shocks, exchange rate, and repayment vehicle yield for stress testing. The interest rate hike scenario had the strongest impact (even in the short term) because about two-thirds of debtors in Austria have floating rate loans. The scenario of rising unemployment showed rather moderate consequences. On the one hand, homeowners are much less likely to become unemployed than renters. Similarly, [Sugawara and Zaldueño, 2011](#) studied the debt sustainability of Croatian households. As it turned out, household debt is not a deterrent to economic activity in the country, shocks do not affect the welfare of households, but increase the likelihood of their bankruptcy on credit obligations. The study's calculations should primarily focus on the increased vulnerability of households to shocks and may represent an upper bound on the financial stability risks Croatia faces from household debt. [Bilston et al \(2015\)](#) for the Bank of Australia, on the other hand, based their analysis on microdata and concluded that the debt burden of the population had increased, but it was concentrated among households able to service debt obligations. This indicates that household debt aggregates may be

misleading about the financial fragility of the entire household sector, rather than some specific part of it. The results of the study also highlight the scope for an expansionary monetary policy to offset the negative impact of (a) rising unemployment and (b) depreciation of household assets, leading to higher loan servicing. The results of stress testing conducted by [Malovana et al \(2017\)](#) for the Bank of the Czech Republic showed that low-income households with mortgage loans taken during a period of low interest rates on them have risks in servicing loan obligations. Thus, in the event of an increase in interest rates, which will not be accompanied by a corresponding increase in the income of the indicated households, there is a threat of an increase in the amount of payments on loans. Moreover, it is the mortgages of the lowest-income households that cause excessive debt burdens.

From the developing countries, in Mongolia, an assessment of the financial resilience of the household sector to macroeconomic shocks showed that the sector is vulnerable to shocks related to interest rates, the cost of essential goods, asset prices, and unemployment ([Doojav and Bayarjargal, 2017](#)). In particular, the debt obligations (or expected credit losses) of households are significantly affected by interest rates and consumer prices. In addition, a significant increase in household debt has been found to have led to financial instability in the household sector. These results have important policy implications for mitigating the growing financial instability of the household sector and risks to financial stability. The Bank of Chile ([Alfaro, 2018](#)) also notes that negative income shocks associated with unemployment (as opposed to price shocks) are the best predictors of mortgage defaults. The conducted stress testing made it possible to reproduce the increase in default on consumer loans observed during the global financial crisis of 2008–2009. Calculations show that debt risk increases with an increase in the unemployment rate, as well as with a lower quality of employment.

The closest to our study from the literature are the World Bank ([Tiongson et al., 2010](#)), and the National Bank of Kyrgyzstan ([Aldashev, 2020](#)). The former assesses the impact of the macroeconomic shock from the global crisis of the late 2000s on household welfare in a number of countries in Europe and Central Asia, including household income flows, consumption levels, and liabilities. In the latter, in addition to other shocks described in the literature, an important part was the shock of the decline in remittances, which is not relevant for Kazakhstan. Moreover, the report for the Kyrgyz Republic states that poor households have been hit the hardest due to the fact that they are also considered net food consumers with limited access to agricultural assets and inputs.

3. Background

Since its independence in 1991, the Republic of Kazakhstan, the largest landlocked country, had seen rapid economic growth that was based largely on its rich natural resources, strong foreign direct investment, and market-oriented reforms. All of these propelled the country into an upper middle-income group by raising standards of living for households. The economic growth, however, was not even across the regions and carried several vulnerabilities. The raising inequality across urban and rural areas became more pronounced and could carry significant risks for the financial system of the country, as similar shocks might vary both in size and scale for households from these two geographies. We, therefore, choose to present our results with a breakdown by urban and rural households across all scenarios.

According to CEIC Data, in Kazakhstan, the level of household debt for 2009–2018 decreased from 13.76 percent to 8.9 percent of nominal GDP. However, the dynamics from the second quarter of 2018 to

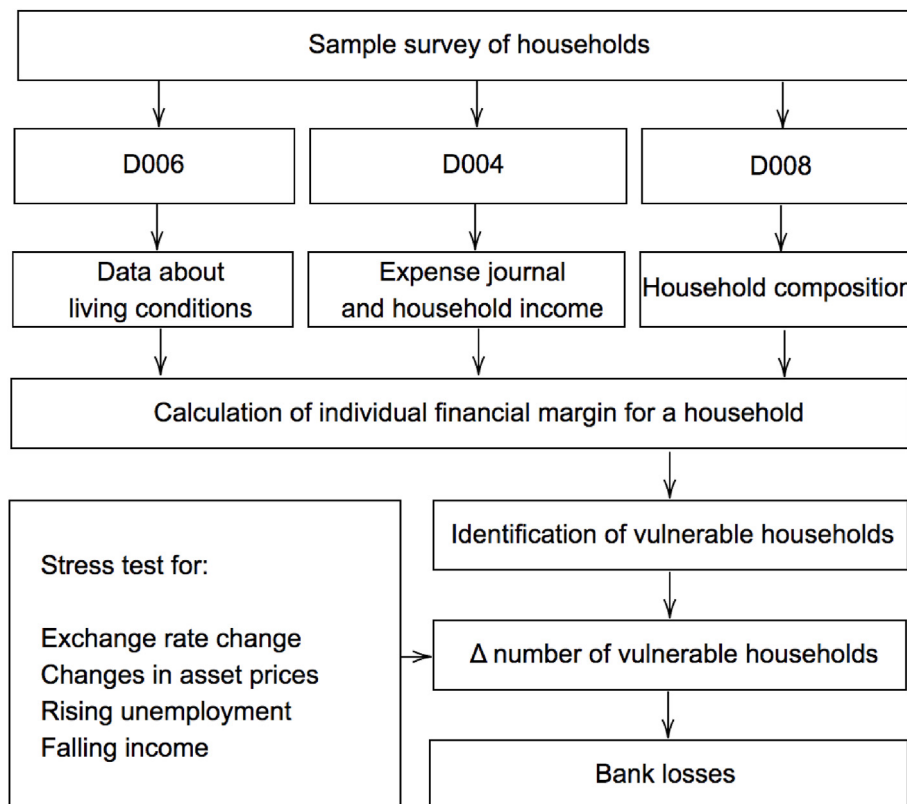


Fig. 1. Schematic representation of the data modules and analysis.

October 2020 show an increase to 10.8 percent.¹ Using the data from the credit registry, Ybrayev et al. (2023) show that the trend is increasing for both individual and corporate loans in Kazakhstan over the similar time period. More importantly, the breakdown by credit borrower type shows that the amount of household credit surpassed corporate (non-bank) business lending in October 2020 for the first time. Hence, this change highlights the increasing role of the household sector in the financial system of Kazakhstan. As a result, the over-indebtedness of households and their resilience to various shocks constitute an issue of vital importance.

Among various shocks discussed in the literature, having a main income-generating job could arguably be viewed as one of the most important factors in the financial sustainability of households. The loss of a job is a severe shock that can result in a household being unable to pay its debt obligations. From 2009 to 2020, the overall unemployment rate has been falling from about 6.5 percent to less than 5 percent (see, Fig. 2). Prior studies, such as Albacete and Fessler (2010), for instance, examined the increase in the overall unemployment rate by 1, 2, and 3 percentage points. Given the historical trends in unemployment rates in Kazakhstan, we would focus on assessing similar scenarios where the unemployment rate changes in increments of 1 percentage point.

In addition, the unemployment statistics could potentially mask the fact that most of the employed population is actually “self-employed”. For instance, at the end of 2019, the number of “working for themselves,” according to the statistics committee, exceeded 2.3 million people.² This category in many ways perhaps

may not differ much from the unemployed. Therefore, in addition to the job loss shock, this study will also consider the income shock. Specifically, we consider scenarios where 20% of households would lose 30%, 40%, and 50% of their income.

In the context of developing countries with heavy reliance on natural resource extraction, currency devaluation is another important shock to consider. Aside from generating public outrage, it usually leads to higher inflation. Rising prices, in turn, lead to higher spending on basic consumption. A recent working paper Colicev et al. (2022) examines the depreciation of the Kazakh tenge against the US dollar in August 2015. The study estimates exchange



Fig. 2. Historical unemployment rate in Kazakhstan from 2009 to 2020. Source: Bureau of National Statistics of the Agency for Strategic Planning and Reforms of Kazakhstan.

¹ Source: <https://www.ceicdata.com/en/indicator/kazakhstan/household-debt-of-nominal-gdp>.

² According to the World Bank, World Development Indicators database, the total labor force in Kazakhstan was about 9.23 million people in 2019. Source: <https://data.worldbank.org/indicator/SL.TLF.TOTL.IN?locations=KZ>.

rate pass-through into consumer prices (i.e., the elasticity of consumer prices to exchange rate changes) to be in between 0.5 and 0.6 12 months after the devaluation. This is an estimate of the exchange rate pass-through obtained at a very large depreciation (approximately 60% against USD/KZT) and is therefore likely to be suitable for simulations in which exchange rate changes take on similar magnitudes, due to the fact that the effect of depreciation can be non-linear. Fig. 3 shows the dynamics of the US dollar to KZT exchange rate, where the devaluation of the national currency is clearly seen. One visible change in the figure is when the Kazakh tenge switched from a fixed to a floating exchange rate regime back in August 2015. In line with such history, we would examine the effect of two types of currency devaluations, 10 and 50 percent. These two estimates should provide ample evidence for potential risks that small and moderate cases would entail for households.

4. Data

We use quarterly household survey data from Kazakhstan for 2019. The dataset is based on the Country Household District Survey conducted by the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan, according to forms D004, D006, and D008. We chose the 2019 wave because it was the most recent wave available to us. It must be noted that the household survey collected by the Bureau of National Statistics does not have a panel structure.

The quarterly questionnaire D004 consists of several parts: (1) expenses on clothes, fabrics and shoes, (2) expenses on household items, appliances, furniture and other expenses for the quarter, (3) housing and communal expenses, (4) education Expenditures, (5) healthcare Expenses, (6) personal and miscellaneous expenses, (7) transport services, (8) transfers and assistance, (9) crop and livestock production, (10) production of goods and services, (11) employment, (12) household income, and (13) borrowed funds.

The data set is initially divided into several files in parts, which we later combine. Data on income were obtained from Module 11 of the Household Survey according to Form D004. Sources of income included income from employment, income from self-employment, income from the sale of real estate, income from the sale of personal property, income from property, dividends, contributions, royalties, rental income from housing, income from the rental of land, agricultural machinery, subsidies and benefits, as well as all kinds of transfers (pensions, scholarships, targeted social assistance, benefits, etc.). The amounts from each of the sources

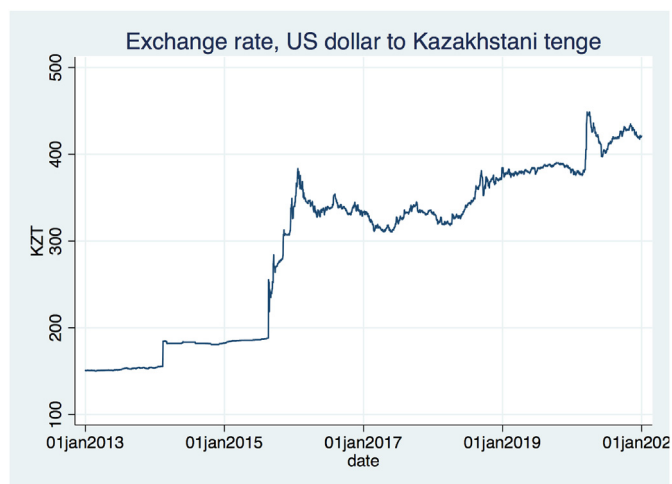


Fig. 3. Historical exchange rate, US dollar to Kazakhstani tenge, from 2013 to 2021. Source: Official (market) Foreign Exchange Rates of the National Bank of Kazakhstan.

were then added together to obtain the total household income.

Since Form D004 does not contain information on household composition, we merged it with the Form D008, the National Statistical Survey Household Composition Checklist. This form includes general information about the household and its members. Using this form, we calculated the size of the household.

We also used statistical form D006, the “Principal Interview Questionnaire.” This form includes information on the type of housing in which the respondent lives (rents), as well as its characteristics, including questions on the improvement of the occupied housing. To extrapolate the sample survey data to the general population, we used sample weights of households in our calculations.

Fig. 1 shows a schematic representation of the various stages of our analysis. As we described above, we then used the data from the above three forms to calculate the variables defined in the next section.

The final dataset is based on the survey contains information on household income and transfers, consumption, housing, debts and household production. We use information on household income, employment status of individual household members and housing, namely potential resale value, in our calculations. The original sample size consists of 12,000 households. But the effective sample size is 11,020 households because of the missing data for some of the variables we used. Sources of income included income from employment, income from self-employment, income from the sale of real estate, income from the sale of personal property, income from property, dividends, contributions, royalties, rental income from housing, income from the rental of land, agricultural machinery, subsidies and benefits, as well as all kinds of transfers (pensions, scholarships, targeted social assistance, benefits, etc.). The amounts from each of the sources were then added together and adjusted to reflect the net total household income.³ Table 1 shows the summary statistics for the main variables of interest. Other modules of the survey with information on household composition, type of housing in which the respondent lives (rents), as well as its characteristics, were merged for final use. To extrapolate the sample survey data to the general population, we used sample weights of households in our calculations. The dataset also contains information on household debts and debt service. The last data source we used was the data on the cost of living which are available at a district level and provided by the Bureau of National Statistics.⁴

5. Methodology

5.1. Financial margin

Based on the prior studies, we define household financial margin FM_i as

$$FM_i = Y_i - BC_i - DS_i \quad (1)$$

where Y_i is household disposable income, BC_i is basic consumption, and DS_i is debt service. BC_i must cover the minimum base

³ We withheld 10% out of employees' gross income for pension contribution and applied a flat rate of 10% to applicable types of personal income, and hence, use disposable income in our simulations.

⁴ The minimum subsistence level is calculated by the government for districts and is based on the sum of the cost of the food basket and the cost of spending on non-food products and services. The former part is based on scientifically based physiological norms of food consumption and the latter on the specific formula. For more details on calculating the subsistence minimum: <https://adilet.zan.kz/rus/docs/V1500011944#z2>.

Table 1
Summary statistics for main variables of interest (in 2019 tenge).

	Disposable income	Debt	Share of HH with debts	Income of HH with debts
Yearly average	494298	413473	0.02	541456
N	11587	222	222	222

consumption.⁵

5.2. Probability of default, exposure to default and loss in the event of default

The percentage of vulnerable households is a key metric for monitoring household resilience to various shocks, such as employment shocks and changes in asset prices or exchange rates. In order to measure the possible losses of banks under various stress scenarios, we need to take into account the share of the total debt of vulnerable households, as well as their assets. For each household, we enter the indicator V_i , which is set to 1 for the vulnerable household ($FM_i < 0$), while the value 0 is assigned to other households ($FM_i \geq 0$). We can now determine the default risk (EAD), which measures the share of debt of vulnerable households in total debt in population,

$$EAD = \frac{\sum_i V_i D_i}{\sum_i D_i} \times 100 \quad (2)$$

where D_i is the debt of household i . This variable can also be interpreted as a share of potentially irrecoverable debts. It is worth noting that households may have assets that can be used to pay off debt, such as real estate. Therefore, we can define the Loss Given Default (LGD) percentage, which measures the proportion of vulnerable households' debt not covered by their real estate to total debt. To do this, we introduce a new variable:

$$NW_i = \begin{cases} D_i - W_i & \text{if } W_i < D_i \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

where W_i is the sum of the household's immovable assets. Thereby,

$$LGD = \frac{\sum_i V_i \cdot NW_i}{\sum_i D_i} \times 100 \quad (4)$$

5.3. Monte Carlo simulation

Consider the idea of the Monte Carlo method in the context of an unemployment shock. The main idea of the Monte Carlo simulation is to generate a new sample based on the current one, where the unemployment indicator is generated from the binomial distribution. That is, each sample is a separate Bernoulli process, with the parameter of the Bernoulli distribution, $p = u + \Delta$, equal to the actual proportion of unemployed in the sample plus the specified change. For example, if the current unemployment rate is 5 percent and you want to determine how the vulnerability of households will change with a 1 percentage point increase in unemployment, then you need to set the distribution parameter to $\Delta = 0.01$. Thus,

⁵ We used the cost of living published by the Bureau of National Statistics for 2019 for each district as the cost of basic consumption BC_i . We relied upon the basic consumption because it is in line with the literature. By using the basic consumption, the analysis would provide us with the lower bound estimates of the effects from these shocks. In addition, the logic of using the basic consumption could also stem from the fact that households could adjust their consumption when faced with one of the stress scenarios.

with each new generation of the sample, the total share of the unemployed does not change (it is fixed at the level of p), but the distribution of employment among individuals changes. If an individual in the newly generated sample is unemployed, then his income is equal to zero, which accordingly affects the financial margin of the household. If the financial margin becomes negative in this case, then the household in this case will be at risk.

Based on the results of multiple samples, the average default risk is calculated, as well as the average default loss. In the literature, there are two approaches to choosing the parameter of the binomial distribution. In the first case, this parameter is the same for all observations, that is, each individual has the same probability of becoming unemployed. In the second case, this probability is different for each individual. To estimate individual probability, a probit regression model is used: $Pr(u = 1) = \Phi(X\beta)$, where X is the matrix of socio-demographic characteristics of an individual, and Φ is the standard normal distribution function. The literature suggests using the following characteristics in probit regression: gender, education level, age, and region.

We run a probit regression $Pr(u = 1) = \Phi(X\beta)$, where X includes binary indicators of gender, region of residence, as well as age and the square of age. Based on this regression, the estimated values of the β vector are calculated. Based on the estimated value, the estimated probability for each household member $\Phi(X\hat{\beta})$ is calculated. Further, having an individual probability estimate for each member of the household, the unemployment indicator is generated from the binomial distribution with the given parameter $p = \Phi(X\hat{\beta})$.

6. Descriptive results

Our first step was to calculate the income, Y , as in equation (1), based on the data described in section 4. This variable includes income from employment, self-employment, income from the sale of agricultural products, income from the sale of various assets, dividends, interest on deposits, royalties, rental income and various transfers. As we have already mentioned, we used disposable income for our estimations, that is, income net of taxes and mandatory payments such as contributions to the pension fund.

Our variable DS , in equation (1), is the debt service (PAID_LOAN), which is the amount a household pays to service its debt. Unfortunately, the questionnaire was designed in such a way that if a household could not make a payment on a loan in the current quarter, then the information on the amount that the household had to repay the loan is unavailable. Therefore, we needed to impute the missing values with estimated ones. To do this, we run the following regression:

$$\begin{aligned} PAID_LOAN_i = & \beta_0 + \beta_1 EMPL_i + \beta_2 SELF_EMPL_i + \beta_3 LOAN_i \\ & + \beta_4 NUM_CHL_i + \beta_5 City + \sum_{k'} \delta_k OBLAST_k \\ & + \sum_{l'} \varphi_{l'} RAYON_{l'} + \varepsilon_i \end{aligned} \quad (5)$$

where NUM_CHL is the number of household members, $City$ is a

Table 2

Base scenario. This table shows the average percentage of vulnerable households for four quarters of the year.

All	Urban	Rural
% vulnerable hh	% of vulnerable hh	% of vulnerable hh
30	24	37

dummy variable of 1 for urban and 0 for rural, and region and district fixed effects, OBLAST and RAYON, respectively.⁶ Replacing zeros with estimated values will give us a lower financial margin estimate.⁷

The basic consumption variable, BC , in equation (1) was based on the minimum cost of living by district. Using equation (1), we enter a default indicator for each V_i household. As described in section 5.2, default indicator 1 is assigned to the vulnerable household ($FM_i < 0$), while default indicator 0 is assigned to other households ($FM_i \geq 0$). Thus, we can calculate the proportion of vulnerable households by quarter and for urban and rural areas. Table 2 below shows the average results across quarters.

The proportion of households identified as vulnerable is 30%, which seems plausible. Although we report the average of these estimates for four quarters of the year, these figures are expectedly lower in urban areas than in rural areas in all four quarters. These estimates are somewhat higher than results from other developing countries, such as Mongolia. Specifically, Doojav and Bayarjargal (2017) estimate the share of households with negative financial margins at about 14 percent in 2014. In Finland, this number vary from 13 to 19 percent for 2000–2004 (i.e., Herrala and Kauko, 2007), still less than our estimates.

After calculating the share of vulnerable households, we can determine the default risk size (EAD), which measures the percentage share of the total debt of vulnerable households, as indicated in equation (2). Subsequently, we could estimate the Loss Given Default (LGD) percentage, which measures the proportion of vulnerable households' debt covered by their real estate, as in equation (4). The table below shows the results of these assessments.

Overall, as shown in Table 3, the average EAD is 35 percent. As expected, EAD estimates for urban households are substantially lower than those for rural households. The estimates of LGD , which is the proportion of vulnerable households' debt that is covered by their real estate wealth, is about 3–4 percent. The estimates for LGD are slightly higher than those from developed countries. For instance, Bilston et al. (2015) for Australia, found them to be 0.8 percent in 2002, 1.2 percent in 2006, and 1.5 percent in 2010. But at the same time, they are also less than those from developing countries, such as Mongolia (i.e., Doojav and Bayarjargal, 2017). There, the estimate was around 7.2 percent for 2014. Naturally, the LGD estimates might vary from other studies due to collateral that is assumed to be recoverable. In both studies that we compare to, it is real estate only.

7. Stress scenarios

7.1. Exchange rate change

The devaluation of the national currency is one of the main shocks for households in Kazakhstan. Historically, there have been

⁶ Oblast refers to administrative region of the country, and Rayon is a subdivision of an oblast.

⁷ We also used a different specification for robustness by including additional variables such as number of children and age. The results (not reported) from alternative specifications are qualitatively similar.

Table 3

Base scenario. This table shows the average EAD and LGD scores across quarters. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

	All	City	Rural
EAD	0.35	0.29	0.44
LGD	0.04	0.04	0.03

several cases of sharp changes in the exchange rate. The impact of this change cannot be estimated directly, but can potentially be detected indirectly using estimates of the exchange rate pass-through to consumer prices. In other words, using the exchange rate elasticity of consumer prices, we could infer the impact on the cost of the consumer basket.

Using the estimate from Colicev et al. (2022), we could analyze how a large currency devaluation of the same order could indirectly affect underlying consumption through inflation, and thus, change the share of vulnerable households and subsequent EAD and LGD estimates. One of the indicators of inflation is the price index. Thus, the formula for calculating inflation is:

$$\pi = \frac{PI_1 - PI_0}{PI_0} \quad (6)$$

where PI_1 and PI_0 are the price indices in the current and last period, respectively. Since the calculated elasticity and devaluation effect occur after 12 months, we will make calculations for the 4th quarter of 2019, thus assuming the shock to have taken place in the 1st quarter. In the first option, we assume that there is a 10% devaluation of the currency. Therefore, using the above expression for inflation, we could calculate the new levels of basic consumption as follows:

$$BC_{new} = BC_{q4}(\eta + \pi + 1) \quad (7)$$

where η is equal to 0.05 for a 10% devaluation case. Official inflation (π) was 5.4 percent. A change in the cost of living will change the underlying consumption variable BC in equation (1) and therefore affect the household financial margin, FM . The results are presented in Table 5 below.

The results show that most values have increased compared to Table 4, which shows the baseline for Q4 of 2019. The value of LGD remained unchanged. The value of EAD increased by 3 percentage points.

If instead we consider a large currency devaluation of 50 percent, then we use the $\eta = 0.25$ value in equation (7) for our calculations. Thus, our results will become as shown in Table 6 below.

It is worth noting that the exchange rate pass-through estimate we use is based on a very large depreciation (approximately 60%), and therefore, this 50% devaluation scenario is more plausible, as it is close to the change in the exchange rate used in the study. This is due to a possible non-linear effect. However, the results from the table show that the scores have increased compared to the previous case. EAD increased by 7 percentage points. LGD increased by 1

Table 4

Base case for Q4 2019. This table shows EAD and LGD estimates. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

Q4 (Base case)	All	City	Rural
EAD	0.32	0.35	0.28
LGD	0.02	0.03	0.00

Table 5

10% devaluation shock. This table shows the EAD and LGD estimates. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

Q4 ($\Delta = 10\%$)	All	City	Rural
EAD	0.35	0.37	0.32
LGD	0.02	0.03	0.00

percentage point compared to the base case but only for urban areas. Relative to developed countries, such as in Austria by [Albacete and Fessler \(2010\)](#), these results are substantially higher. Namely, for Austrian households, the study finds that a 5% devaluation increases the EAD from the baseline of 14.3%–15.1%, less than a percentage point increase.

7.2. Changes in asset prices

Changes in asset prices are a shock to the wealth of households or their assets. Such changes, in principle, should affect only LGD. Thus, here we are considering a shock when the price of an asset falls by 10%, 20%, and 30%. The results of this script are shown in [Table 7](#) below.

Compared to the base case, LGD performance did not change in all cases, with only a slight increase for rural LGD given 30% fall in the price of assets. The rest of the scores seem to be comparable to the base scenario in [Table 3](#). In Australia, on the other hand, a 10 percent decrease in asset prices increased debt and risk by 0.4 percentage points. And a more substantial decrease of 50% lead to an increase by 5 percentage points. In Mongolia, on the other hand, a similar 30 percent decrease in housing prices increased the debt at risk by 0.73 percentage points ([Doojav and Bayarjargal, 2017](#)).

7.3. Rising unemployment

When a working member of a household loses a job, this affects household income Y , in equation (1). Since not every working person in the economy has the same probability of becoming unemployed, we first need to determine the probability for every working individual in our sample to become unemployed. To assess individual probability, a short probit regression model is used, which includes the socio-demographic characteristics of the individual, such as gender, age, and region. Next, having an individual probability estimate for each member of the household, an unemployment indicator is generated from the binomial distribution. If, in the newly generated sample, a household member who was employed in the original sample becomes unemployed, then his income is reset to equal the unemployment benefit and household income is recalculated. The methodology is described in more detail in section 5.3. All vulnerability indicators, EAD and LGD are recalculated given updated incomes. In this case, the scenario will include increases in the unemployment rate (UR) by 1, 2, and 3 percentage points. The value of the unemployment benefit is individual-specific and is described below.

The government grants a social payment in case of a job loss with the amount that is based on the historical monthly income.

Table 6

50% devaluation shock. This table shows the EAD and LGD estimates. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

Q4 ($\Delta = 50\%$)	All	City	Rural
EAD	0.39	0.42	0.36
LGD	0.02	0.04	0.00

Table 7

The price of an asset falls by 10%, 20%, and 30%. This table shows LGD scores. The LGD values represent the proportion of vulnerable households' debt that is covered by their real estate wealth.

Decrease in Asset Prices	All	City	Rural
	LGD	LGD	LGD
10%	0.04	0.04	0.03
20%	0.04	0.04	0.03
30%	0.04	0.04	0.04

But there is a maximum limit on the average monthly income that is taken into account. More specifically, the social contributions should not exceed 7 times the minimum wage (e.g., that is 42,500 tenge in 2019). Hence, the amount of the social payment in case of a job loss is determined by multiplying the average monthly income in the last 24 months by the appropriate income replacement rates and the participation rate. The latter two might vary depending on duration of social contributions, etc. Since we have no information on past income to calculate the average income over the last 24 months and no information on past social security contributions we assume that the income did not change in the last 24 months. The duration of payments to the social security system also affects the size of the unemployment benefit. This will be especially important if a person only contributed to social security for less than 6 months. For this very vulnerable group the size of the unemployment benefit would be 8 times less than for someone who contributed for more than 24 months *ceteris paribus*. Since we have no information on the duration of social security contributions of individuals in the data our estimates will constitute a lower limit with EAD and LGD being potentially higher if we have substantial shares of individuals who contributed to the social security for less than 6 months.

In our simulations, we implement the following steps: when a new sample is drawn, then a person (previously employed) becoming unemployed has his or her employment income trimmed to $0.45 \times$ employment income (i.e., the coefficient times the income). If this product exceeds 7-fold minimum wage, then his or her new employment income will be set to 7×42500 or to 297,500 tenge.

After 200 simulations, we get 200 new values for each vulnerability parameter, over which we find the average value. The results of these simulations are shown in [Table 8](#).

The EAD value, on average, increased by 1 percentage points from 35 percent to 36 percent. For urban households the EAD virtually did not change. As for rural households, the change in EAD is only about 1 percentage point. These results are comparable to other studies. For instance, in Mongolia, the effect of a 1 percentage point increase in unemployment rate resulted in increase of debt at risk of 0.48 percentage points ([Doojav and Bayarjargal, 2017](#)). In Austria, by [Albacete and Fessler \(2010\)](#), an increase of 1, 2, and 3 percentage points in unemployment rate, led to an increase in average EAD by 0.1, 0.2, and 0.3 percentage points, respectively. Similar to our results, the LGD estimates didn't change in their study.

7.4. Falling income

In this section, we run a Monte Carlo simulation of a scenario in which 20% of households lose 30%, 40%, and 50% of their income (employed, self-employed, and agricultural income). The simulation results are shown in [Table 9](#).

The EAD value, on average, increased by 3 percentage points from 35 percent to 38 percent, with a 30 percent drop in income. A

Table 8

Increases in the unemployment rate by 1, 2, and 3 percentage points. This table shows the average EAD and LGD scores for the year. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

pp increase		All	City	Rural
1pp	EAD	0.35	0.29	0.44
	LGD	0.04	0.04	0.03
2pp	EAD	0.35	0.29	0.44
	LGD	0.04	0.04	0.03
3pp	EAD	0.36	0.29	0.45
	LGD	0.04	0.04	0.03

Table 9

20% of households lose 30%, 40%, and 50% of income. This table shows the average EAD and LGD scores for the year. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

drop of		All	City	Rural
30%	EAD	0.38	0.31	0.47
	LGD	0.04	0.04	0.04
40%	EAD	0.39	0.34	0.47
	LGD	0.04	0.04	0.04
50%	EAD	0.43	0.37	0.51
	LGD	0.04	0.04	0.04

40% and 50% drop in income increases this figure to 39% and 43%, respectively. However, for urban areas, the figure is 31% for a 30% drop in income and 34% and 37% for a 40% and 50% drop in income, respectively. For rural areas, the EAD is 47% for a 30 percent drop in income and 47 and 51 percent for a 40 and 50 percent drop in income, respectively. At the same time, the LGD indicator did not change significantly.

7.5. Results by income quartiles

In this section we take into account the household income heterogeneity. Specifically we break down households into income quartiles and repeat the simulations to get an idea how different households are affected by shocks.

The descriptive results in [Table 10](#) show considerable heterogeneity among households of different income groups. We can see that vulnerability measured by EAD monotonically decreases with income. Both urban and rural households in lower income quartiles are more vulnerable than households in upper quartiles. However, there is some non-monotonicity in LGD measures. The highest value of LGD of 12% is observed for the third quartile. This indicates that the households in the third quartile in rural areas have

Table 10

Baseline estimates by income quartile. This table shows the average EAD and LGD scores by income quartiles. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

Income Quartile		City	Rural
Q1	EAD	0.73	0.80
	LGD	0.06	0.01
Q2	EAD	0.43	0.65
	LGD	0.04	0.02
Q3	EAD	0.26	0.39
	LGD	0.03	0.12
Q4	EAD	0.16	0.30
	LGD	0.04	0.00

Table 11

Increase in the unemployment rate (UR) by 1, 2, and 3 percentage points by income quartiles. This table shows the average EAD and LGD scores for the year. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

Income Quartile	UR increase		City	Rural
Q1	1pp	EAD	0.73	0.80
		LGD	0.06	0.01
	2pp	EAD	0.73	0.81
		LGD	0.06	0.01
	3pp	EAD	0.73	0.81
		LGD	0.06	0.01
Q2	1pp	EAD	0.43	0.65
		LGD	0.04	0.02
	2pp	EAD	0.43	0.66
		LGD	0.04	0.02
	3pp	EAD	0.43	0.66
		LGD	0.04	0.02
Q3	1pp	EAD	0.26	0.39
		LGD	0.03	0.12
	2pp	EAD	0.27	0.40
		LGD	0.03	0.12
	3pp	EAD	0.27	0.40
		LGD	0.03	0.12
Q4	1pp	EAD	0.16	0.31
		LGD	0.04	0.00
	2pp	EAD	0.16	0.31
		LGD	0.04	0.00
	3pp	EAD	0.17	0.31
		LGD	0.04	0.00

significant debt which is not backed up by enough collateral.

The results from unemployment shock by income quartiles are shown in [Table 11](#). The estimates indicate that the increase in unemployment affects the EAD and LGD only marginally.

The estimates in [Table 12](#) show significant effects of income losses on EAD measures across all quartiles. The change in the first quartile is relatively small, about 2–3 percentage points for both urban and rural households. In the second quartile the increase in EAD is about 5 percentage points for both urban and rural households. In the third quartile the change in EAD is larger, about 8–9 percentage points. In the fourth quartile we observe the biggest

Table 12

20% of households lose 30%, 40%, and 50% of income. This table shows the average EAD and LGD scores by income quartiles. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

Income Quartile	Drop of		City	Rural
Q1	30%	EAD	0.75	0.82
		LGD	0.06	0.01
	40%	EAD	0.75	0.82
		LGD	0.06	0.01
	50%	EAD	0.76	0.82
		LGD	0.06	0.01
Q2	30%	EAD	0.45	0.68
		LGD	0.04	0.03
	40%	EAD	0.46	0.69
		LGD	0.04	0.03
	50%	EAD	0.48	0.70
		LGD	0.04	0.03
Q3	30%	EAD	0.30	0.43
		LGD	0.03	0.12
	40%	EAD	0.32	0.45
		LGD	0.03	0.12
	50%	EAD	0.35	0.47
		LGD	0.03	0.12
Q4	30%	EAD	0.18	0.32
		LGD	0.04	0.00
	40%	EAD	0.21	0.32
		LGD	0.04	0.00
	50%	EAD	0.26	0.37
		LGD	0.05	0.00

Table 13

Increases in the unemployment rate by 1, 2, and 3 percentage points and a devaluation shock of 10% and 50%. This table shows the average EAD and LGD scores for the year. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

devaluation	pp increase		All	City	Rural
10%	1pp	EAD	0.40	0.34	0.47
		LGD	0.04	0.04	0.03
	2pp	EAD	0.40	0.35	0.47
		LGD	0.04	0.04	0.03
	3pp	EAD	0.40	0.35	0.48
		LGD	0.04	0.04	0.04
50%	1pp	EAD	0.45	0.39	0.52
		LGD	0.04	0.04	0.04
	2pp	EAD	0.45	0.39	0.52
		LGD	0.04	0.04	0.04
	3pp	EAD	0.46	0.41	0.53
		LGD	0.04	0.04	0.04

effect for urban households for whom the EAD increases by 10 percentage points. For rural households in the fourth quartile EAD increases by 7 percentage points. The LGD measures are unaffected across all quartiles.

7.6. Combined scenarios

In this section, we consider combined shocks scenarios. In particular, we look at two cases: rising unemployment and a devaluation shock, and falling incomes and devaluation.

7.6.1. Rising unemployment and devaluation shock

Using the procedure described in 7.1 and 7.3, here we consider a 1, 2, or 3 percentage point increase in unemployment combined with a currency devaluation of 10 or 50 percent. The results are summarized in Table 13.

EAD values, which were 35 percent in the base case, increased on average for all by about 5 percentage points. LGD values remain virtually unchanged.

7.6.2. Falling incomes and devaluation shock

The second combined scenario we considered was a fall in income (where 20% of households lose 30%, 40%, and 50% of income) combined with devaluation (a 10% and 50% shock).

EAD values have increased significantly, ranging from an increase of 5 percentage points to about 18 percentage points as shown in Table 14. For urban households, the increase was 8–18 percentage points, and for rural households, 5–15 percentage points. On the other hand, the increase in LGD was not so significant and increased by only about 1 percentage point.

Table 14

20% of households lose 30%, 40%, and 50% of income and a devaluation shock of 10% and 50%. This table shows the average EAD and LGD scores for the year. The EAD and LGD values represent the proportion of vulnerable households' debt that is uncovered and covered by their real estate wealth, respectively.

devaluation	drop of		All	City	Rural
10%	30%	EAD	0.42	0.37	0.49
		LGD	0.04	0.04	0.04
	40%	EAD	0.44	0.40	0.51
		LGD	0.04	0.04	0.04
	50%	EAD	0.47	0.41	0.54
		LGD	0.04	0.04	0.04
50%	30%	EAD	0.48	0.43	0.56
		LGD	0.05	0.05	0.04
	40%	EAD	0.50	0.45	0.57
		LGD	0.04	0.05	0.04
	50%	EAD	0.52	0.47	0.59
		LGD	0.05	0.05	0.04

8. Conclusion

The increase in household debt in recent years has raised questions about the sustainability of this debt and possible risks to the banking sector. As several different crises around the world, including the US mortgage crisis, have shown, even a relatively small number of indebted households can cause major shocks if their debt sustainability is in question.

Given the limitations of using macro statistics, we use micro data based on 2019 quarterly household survey data to analyze potential risks to Kazakhstan's financial stability. Stress tests based on household data can better show the mechanisms of possible default at the micro level and therefore can help identify groups of debtors that are particularly vulnerable. The stress tests performed in this study are likely to be better suited for assessing EAD and LGD performance and help to get an idea of the potential losses of the banking sector under various scenarios. Moreover, they can show which shocks are especially dangerous for households.

In this study, we analyzed four stress scenarios: exchange rate changes, rising unemployment, asset price changes, and falling incomes, as well as combined scenarios. Moreover, we explored two dimensions of household heterogeneity: urban vs. rural and by income quartiles. Based on EAD estimates the rural households turned out to be more vulnerable than urban ones. Not surprisingly, the households in the lowest income quartiles have the highest EAD estimates. For the falling income shock, the EAD value, on average, increased by 3 percentage points from 35 percent to 38 percent, with a 30 percent drop in income. A 40% and 50% drop in income increases this figure to 39% and 43%, respectively. At the same time, the LGD indicator did not change significantly. A relatively small devaluation of 10% lead to an EAD increase of 3 percentage points from the base case, with 2 and 4 percentage points increase for urban and rural households, respectively. The large currency devaluation of 50% however, leads to an EAD increase of 7 percentage points with 6 and 8 percentage points increase for urban and rural households, respectively. On the other hand, the rising unemployment gave rise to EAD estimates of about 1 percentage point from the base case.

It should be noted that the quality and the stability of estimates obtained depends on the quality of the data. Thus, even the micro household data might have its limitations. For instance, we do not have information about the amount of debt that must be paid in a quarter if the household is unable to pay the debt. Accordingly, we had to rely on the proxy of these values using equation (5). If data on the amount of debt to be paid were asked directly, the quality of the estimate would be higher. To calculate LGD, an appraisal of the value of real estate is required. In the data of the Bureau of Statistics, the estimate of the value at which it is possible to sell real estate owned by the household was recorded from the words of the household, which might also introduce some noise into the results. Also, in addition to real estate, households may have other assets that can be sold to service debt, such as a car or household appliances. Unfortunately, there is no information on the value of these assets in this questionnaire. Therefore, more comprehensive surveys are needed, including detailed information on the diversity of household assets and liabilities, ideally in panel form.

Appendix. robustness and alternative tests

A.1. Probability of becoming unemployed

As we mention in section 5.3, we run probit regression model, $Pr(u = 1) = \Phi(X\beta)$, where X is the matrix of socio-demographic characteristics of an individual, and Φ is the standard normal distribution function. And based on estimated values, we calculate the

probability of becoming unemployed for each household member, $\Phi(X\hat{\beta})$. Here we provide results from this specification by each quarter.

Table 15
Probit regressions

Variable	Q1		Q2		Q3		Q4	
	coef	z	coef	z	coef	z	coef	z
City	0.03	1.1	0.03	1.2	0.03	1.2	0.02	0.7
Female	0.84	31.9	0.93	36.4	0.93	35.8	0.92	35.1
Age	-0.3	-44.3	-0.27	-40.5	-0.26	-38.2	-0.28	-39.2
Age ²	0.004	45.3	0.003	41.3	0.003	39.1	0.003	40
Medium skill	-2.09	-6.7	-1.93	-6.6	-1.64	-6.5	-1.73	-6.5
High skill	-2.84	-9.2	-2.65	-9.2	-2.28	-9.1	-2.45	-9.4
Oblast FE	yes		yes		yes		yes	
N	20538		20692		20079		19643	
Pseudo R2	0.22		0.2		0.19		0.21	

A.2. Alternative vulnerability measures

As a robustness, in this section we use debt service-to-income (DSTI) ratio as an alternative measure of the vulnerability of households, and present the results from the same shocks. [table 16](#) shows the baseline statistics for the debt service-to-income ratios. The average ratio is around 18 percent. For the first scenario that we consider, as described in [section 7.4](#), these ratios increase by 2–3 points. As for the second scenario, as described in [section 7.3](#) results are shown in [table 18](#). Overall, the ratios didn't change much and are equivalent to the ones in the baseline case. Similar to our EAD estimates, the income shock is bigger in magnitude relative to the unemployment shock.

Table 16
Baseline estimates. This table shows the debt service-to-income (DSTI) ratios.

	All	City	Rural
Average DSTI	0.18	0.20	0.16

Table 17
20% of households lose 30%, 40%, and 50% of income. This table shows the debt service-to-income ratios.

	Drop of	All	City	Rural
Average DSTI	30%	0.20	0.22	0.17
	40%	0.20	0.22	0.18
	50%	0.21	0.23	0.19

Table 18
Increase in the unemployment rate (UR) by 1, 2, and 3 percentage points. This table shows the debt service-to-income (DSTI) ratios.

	UR increase	All	City	Rural
Average DSTI	1pp	0.18	0.20	0.16
	2pp	0.18	0.20	0.16
	3pp	0.18	0.20	0.16

References

- Albacete, Nicolas, Fessler, Pirmin, 2010. "Stress testing Austrian households". In: Financial Stability Report, Oesterreichische Nationalbank (Austrian Central Bank), vol. 19, pp. 72–91.
- Aldashev, Alisher, 2020. "Stress testing of the household sector of the Kyrgyz Republic based on the use of microdata". In: National Bank of the Kyrgyz Republic.
- Alfaro, Rodrigo, 2018. "Stress testing Chilean corporate and household sectors". In: Central Bank of Chile.
- Bilston, Tom, Johnson, Robert, Read, Matthew, 2015. "Stress testing the Australian household sector using the HILDA survey". In: Research Discussion Paper 2015-01. Reserve Bank of Australia.
- Colicev, Anatoli, Hoste, Joris, Konings, Jozef, 2022. "The impact of a large depreciation on the cost of living of rich and poor consumers". In: CEPR Discussion Paper No. DP16869.
- Doojav, Gan-Ochir, Bayarjargal, Ariun-Erdene, 2017. "Stress testing the household sector in Mongolia". In: Asia-Pacific Development Journal, vol. 24, pp. 23–52, 2.
- Giordana, Gaston, Ziegelmeyer, Michael, 2017. "Household debt burden and financial vulnerability in Luxembourg". In: IFC Bulletins Chapters, Data Needs and Statistics Compilation for Macroprudential Analysis, vol. 46.
- Herrala, Risto, Kauko, Karlo, 2007. "Household loan loss risk in Finland: estimations and simulations with micro data". In: Bank of Finland Research Discussion Papers 5/2007.
- Johansson, Martin, Persson, Mattias, 2007. "Swedish households' indebtedness and ability to pay: a household level study". In: Proceedings of the IFC Conference on "Measuring the Financial Position of the Household Sector", vol. 26, pp. 234–248. Basel, 30-31 August 2006.
- Malovana, Simona, Hlaváček, Michal, Galuscak, Kamil, 2017. "Stress testing the Czech household sector using microdata - practical applications in the policy-making process". In: Data Needs and Statistics Compilation for Macroprudential Analysis, vol. 46. Bank for International Settlements.
- Sugawara, Naotaka, Zalduendo, Juan, 2011. "Stress-testing Croatian households with debt - implications for financial stability. In: Policy Research Working Paper Series 5906. The World Bank.
- Tiongson, Erwin R., Sugawara, Naotaka, Sulla, Victor, Taylor, Ashley, Gueorgieva, Anna I., Levin, Victoria, Subbarao, Kalanidhi, 2010. The Crisis Hits Home: Stress-Testing Households In Europe And Central Asia. World Bank.
- Ybrayev, Z., Talakin, A., Kairullayev, Y., et al., 2023. Household debt service ratio in a developing economy: borrower-based analytical tools and macroprudential policy overview in Kazakhstan. J Bank Regul. <https://doi.org/10.1057/s41261-023-00218-7>.