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BEFORE THE FALL: HOW UNEMPLOYMENT SHOCKS SHAPE CONSUMER LOAN DEFAULTS

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Abstract

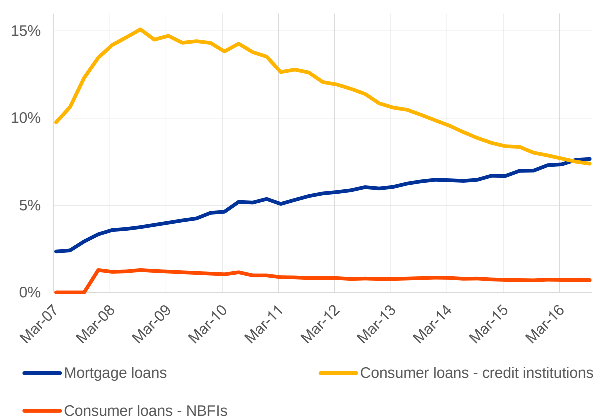
We investigate the impact of an unemployment shock on the probability of default of consumer loans, highlighting the importance of the income category prior to financial distress. Combining a granular credit registry with administrative data regarding debtors' incomes over a seven-year period, we employ a logistic regression to quantify the relationship between job loss and default. We find that, on average, transitioning to unemployment leads to a doubling of the probability of default. However, in the case of debtors at the lower end of the income distribution, an unemployment shock has a much stronger impact, increasing the probability of default to 5%, as opposed to only 2,25% in case of a high-income debtor. We observe a similar pattern in the case of negative income shocks. The results provide valuable insights for policy makers and credit institutions, especially given the important share of low-income debtors with consumer loans.

Keywords: Credit risk, household loans, probability of default, consumer credit, unemployment

INTRODUCTION

Consumer lending is considered riskier compared to housing loans due to several factors. Unlike mortgages, which are secured by real estate and offer a relatively stable collateral value, consumer loans are unsecured, making them more vulnerable to fluctuations in borrowers' financial standing. Our goal is to examine how changes in income and unemployment impact We use a debtor-level dataset for Romania that links administrative earnings data with credit registry information, spanning seven years (2009-2015), including the period after the global financial crisis and the subsequent recovery. As can be seen from Figure 1, consumer loans made up around 70% of household indebtedness in 2009. While this figure decreased over the analyzed period, it still remains significant, representing around 50% of household debt at the end of 2015. Furthermore, given that Romania is a bank-based economy, non-bank financial intermediaries (NBFIs) only have a small share of household loans, therefore our focus on bank lending will give a complete picture of household indebtedness. Furthermore, as Figure 2 shows, there is a strong correlation between the unemployment rate and the probability of default for consumer loans in Romania. Therefore, the quantification of the determinants of probability of default for consumer loans is of great importance for both policy-makers, as well as credit institutions.

Figure 1. Household indebtedness in Romania (% of GDP)



Source: NBR, Eurostat, own calculations

Figure 2. Consumer loans default rate and unemployment rate in Romania

Source: NBR, Eurostat, own calculations

Numerous studies highlight that unemployment and income shocks are important drivers of default. Linn and Lyons (2020) use debtor-level data for mortgages in the European Data Warehouse across five European countries. They find that while negative equity itself is a relatively small contributor to default, the effect of unemployment, and other variables such as the interest rate, is stronger for those in negative equity. Using survey data in the US, Gerardi et al. (2018) find that when both the head of the household and spouse are unemployed, the likelihood of default increases by over 8 percentage points, while the job loss has an impact on the probability of default of the same magnitude as a 35% decrease in equity.

McCarthy (2014) use an administrative loan-level data collected by the Central Bank of Ireland as part of a prudential capital assessment review to examine the impact of labor market conditions, income volatility, and housing equity on mortgage distress in Ireland. Their findings show that while unemployment and negative housing equity are key drivers for default, many borrowers in arrears are employed, but face income declines, unstable contracts, or a history of job insecurity. Therefore, their results point out that addressing mortgage distress requires policies beyond reducing unemployment, focusing also on labor market stability and job security.

However, the number of studies which employ administrative data over multiple years is very limited. Based on Italian micro data from tax records and credit registers, Mocetti and Viviano (2017) show that controlling for credit conditions at origination, job losses nearly double the delinquency risk. Kukk (2023) uses a similar empirical setup in the case of Estonia in order to correct for the selection bias. The paper finds that income shocks were the main drivers in the increase of arrears experienced after Global Financial crisis by Estonia.

O'Toole and Slaymaker (2021) analyze the impact of affordability shock through the economic cycle by using data from the EU Survey on Income and Living Conditions for Ireland between 2004 and 2017. They find that borrowers with a high level of indebtedness are twice as affected by a negative debt service shock. Furthermore, labor market shocks are the main drivers of default during periods of crisis, while during non-crisis period, debt service shocks are more relevant.

We complement existing literature in two ways. First of all, we build upon Nier et al. (2019), which use a similar administrative dataset for Romania. They show that debt service to income (DSTI) has a non-linear impact on the probability of default which becomes positive and statistically significant above 50% for mortgages and 30% for consumer loans. However, they employ data at only one point in time (June 2016), thus not taking into account how changes in borrowers' income and in the business cycle may affect borrower default and recovery. Second of all, we demonstrate that unemployment shocks have an asymmetric effect, depending on the borrower's differently previous income category. As anticipated, we discover that unemployment shocks have a significantly greater impact on low-income borrowers compared to debtors situated in a higher income category.

One explanation for this pattern resides in the fact that high-income borrowers usually have larger savings, allowing them to better withstand job loss. Second of all, low-income borrowers allocate a higher percentage of their incomes to subsistence expenditure, which are fixed and cannot be reduced. Therefore they would be forced to forego paying their loan installments to cover basic necessities such as food or utilities. Furthermore, debtors from lower income categories tend to have higher level of indebtedness, therefore they are much more vulnerable any negative income shock as opposed to high income borrowers.

Finally, it is important to mention that given the short maturity of consumer loans[1], the denomination in local currency[2], as well as the prevalence of fixed interest rates for the entire period of the loans, changes in the debt-service-to-income ratio for debtors can only come from changes in their income. This is in great contrast to mortgages, where the long maturity makes them sensitive to changes in interest rates, while some are denominated in foreign-currency, thus being sensitive to devaluations. Additionally, as the loans analyzed are unsecured, changes in real-estate prices or negative equity concerns would not play any role. Consequently, we are able to precisely identify how an affordability shock would affect the probability of default.

RESEARCH METHODOLOGY

We employ yearly vintages of data spanning between 2009 and 2014. The period was chosen based on data availability for both credit registry information, as well as administrative data regarding wages. Thus we are able to cover both the recession following the Global Financial Crisis[3], as well as the subsequent recovery[4]. Having an overview of both period of recession and growth ensures that we have a through-the-cycle perspective of the determinants of default for consumer loans.

For income data, we use an individual level database from the Ministry of Finance. Regarding loan characteristics, we combine data from Central Credit Register, covering all consumer and mortgage loans above RON 20,000 with the Credit Bureau, a privately owned credit registry which covers loans bellow RON 20,000. The use of the private Credit Bureau data is important, since a significant proportion of consumer loans consist in small amount loans. The data regarding loan and debtor characteristics is taken at December of each year. We include only debtors with unsecured consumer loans, thus excluding with mortgage backed or real estate collateralized consumer loans. This allows us to pinpoint specifically drivers of default for unsecured loans. The two credit registries offer information regarding the outstanding amount, current interest rate, residual maturity, monthly loan installment and currency of denomination. In

[1] Consumer loans in the sample have an average residual maturity of 4,3 years.
[2] Approximately 90% of consumer loans in the sample are denominated in local currency.
[3] In 2009, Romania experienced a contraction in GDP of 5,4%.
[4] By 2014, the Romanian economy was growing by 4,1% on a yearly basis and was 20% larger compared to 2009 levels.

case a debtor has multiple consumer loans, we construct a weighted average of the relevant interest rate and residual maturity. Variables are winsorized at the 2.5% level in order to exclude outliers. The bank of origination and currency information are taken from the largest loan. Regarding debtor characteristics, we have information regarding the age of the borrower and the county of residence.

Only performing loans (i.e. those with less than 90 days past due), are included in the sample. A debtor is classified as defaulted if they have delays greater than 90 days one year from the vintage creation moment. Therefore we monitor defaults which occurred between 2010 and 2015. As we focus strictly on debtors that only have unsecured consumer loans, there is no danger of having negative spillovers from other types of loans.

Data regarding income is collected from the Ministry of Public Finance. We include only salaried employees which have an annual income greater than the minimum wage. After merging the two datasets, our sample contains 6,8 million borrower-level observations across the analyzed period, representing 2.3 million unique borrowers.

The monthly income is obtained by dividing the annual net income of the debtor by 12. The DSTI ratio is calculated as the ratio of the monthly debt service as of December of the respective year by the monthly income. A categorial variable for income is also employed and calculated as follows: i) between the minimum wage and the 30th percentile (representing a proportion of 15% of the dataset-wise borrowers), ii) between the 30th and 60th percentile (i.e. 30% of the dataset borrowers), iii) between 60th and 90th percentile (i.e. 43% of the dataset borrowers) and iv) above the 90th percentile (12% of the borrowers in the database).

The sample excludes borrowers with an annual income below the minimum wage, as well as those which do not have a registered income at the Ministry of at the moment of the vintage creation, as we are interested in capturing the impact of the transition to unemployment. We classify a person as transitioning to unemployment if in the subsequent year the debtor has declared an annual income below the minimum wage income or they did not declare any income to the Ministry of Public Finance.

Overall, there is an average probability of default of 2.1% in the sample. The average probability of default varies between 2.5% and 1.2 % (the highest in 2009 and the lowest in 2014), in line with Figure 2 and the overall evolution of the economy in the observed period.

Table 1 presents the means of main variables in the analysis divided by performance status. As expected, non-performing borrowers have a higher average DSTI (54% vs. 39%) and lower incomes (208 Euros equivalent vs. 303 Euros equivalent). Furthermore, non-performing debtors have a higher likelihood of becoming unemployed (19.5% vs. 8.7%). Non-performing debtors have larger amounts outstanding (3,758 Euros versus 3,512 Euros), corresponding to higher DSTI. Residual maturity and interest rate are similar between the two groups, while non-performing debtors have a slightly higher share of foreign currency denominated loans. Finally, non-performing debtors are slightly younger and a slightly longer residual maturity of loans. Interest rates of non-performing debtors are slightly higher, indicating a higher risk profile.

Table 1. Descriptive statistics by performance status

	Performing debtors		Non-performing debtors	
	No. of observations	Mean	No. of observations	Mean
Income[1]	6,752,257	303	141,194	208
Outstanding amount[1]	6,752,257	3,512	141,194	3,758
DSTI	6,752,257	38.5%	141,194	54.1%
Interest rate	6,752,257	12.5%	141,194	13.0%
Residual maturity[2]	6,752,257	4.3	141,194	4.8
FX	6,752,257	12.4%	141,194	15.3%
Age[2]	6,752,257	41.7	141,194	38.2
Transition to unemployment	6,752,257	8.7%	141,194	19.5%
Delta (Income)	6,162,572	3.4%	113,700	49.6%

Notes: 1) amount in euro, 2) years. Source: Own calculations

Furthermore, we analyze how the main variables of interest differ by income category (Table 2). As expected, the unconditional probability of default decreases as income increases: a debtor in bottom tercile of the income distribution has an average probability of default of 4% compared to 0.8% for those in the upper decile. Furthermore, low-income debtors have a higher degree of indebtedness, as measured by the DSTI ratio, making them even more vulnerable to a potential income or unemployment shock. Finally, we observe that low-income debtors are also more likely to become unemployed as opposed to high-income debtors. This shows that borrowers in lower part of the distribution are much more vulnerable overall.

Table 2. Mean values for main variables by income category

	<p30	(p30-p60]	(p60-p90]	>p90
Number of debtors	1,033,000	2,038,000	2,958,000	865,451
Default	4.0%	2.5%	1.4%	0.8%
Income[1)]	60	167	345	754
Outstanding amount[1)]	2,516	2,441	3,860	6,075
FX	11.6%	9.0%	12.8%	20.2%
DSTI	55.2%	30.2%	24.8%	18.0%
Interest rate	12.9%	12.8%	12.4%	11.9%
Residual maturity[2)]	4.2	4.2	4.4	4.5
Age[2)]	41.5	41.0	41.7	43.3
Transition to unemployment	29.4%	7.4%	4.5%	3.5%

Notes: 1) amount in euro, 2) years. Source: Own calculations

The methodology employed is a logit model. The baseline model is specified as follows:

$$y_{i,t} = \alpha + \beta' * Z_{i,t-1} + \delta' * L_{i,t-1} + \sum_{j=1}^{4} \theta_j \, Income\ category_{\,i,j,t-1} * Transition\ to\ unemployment_t$$
$$+ Bank\ FE + Origination\ FE + County\ FE + Vintage\ FE + \varepsilon_{i,t}$$

Where, the indices *i* and *t* represent borrower and time, respectively. Index *j* refers to the income categories: bellow the 30th percentile, between the 30th and 60th percentile, between the 60th and 90th percentile and above the 90th percentile. The percentiles are taken from the entire distribution of salaried employees and are updated annually. The vector of borrower controls, $Z_{i,t-1}$, includes DSTI, and age with a 1-year lag to the date when default is observed. The vector of loan characteristics, $L_{i,t-1}$, includes lagged outstanding amount, currency of denomination, residual maturity, and interest rate. To control for variations in risk management policies across banks, we include bank and year-of-origination fixed effects. In order to control for macroeconomic shocks and the state of the economy, we include vintage fixed effects. Additionally, county fixed effects are incorporated to control for regional differences in the labor market.

With the aim to evaluate the impact of an unemployment shock, we include a dummy which indicates if the debtor became unemployed over the analyzed period. In order to evaluate whether such a shock may have an asymmetric impact depending on the debtors' previous income category, we interact the unemployment shock with the debtors' income category.

RESULTS

Column (1) in Table 3 refers to our baseline model as detailed in Equation (1). The regression has an AUROC score of 70%, indicating strong predictive power. In line with previous studies and with economic reasoning, we find that a higher interest rate contributes to an increased in the probability of default. Concretely, a 5-percentage point increase in the interest rate leads to a 2.5% increase in the probability of default for the average borrower. The coefficient for residual maturity is also positive and significant: a debtor has more to gain if they default at the beginning of the loan, once they have only repaid a limited amount. Thus, a 1-year increase in the residual maturity translates into a 5% higher probability of default. Debtors with higher amounts are also more likely to default, given a similar reasoning: they have more to gain from not repaying the bank in absolute terms. Thus, a greater outstanding amount by 1,000 Euros is equivalent to a 7% higher probability of default. The coefficient for foreign-currency denominated loans is also positive and significant, indicating that a consumer loan denominated in foreign currency has 27% higher probability of default compared to a consumer loan denominated in local currency. Additionally, older debtors have, on average, a lower probability of default.

Borrowers' indebtedness, as measured by the DSTI ratio, is positive and significant in all specifications5. This is below the estimated effect by Nier et al. (2019), given that according to their results the effect is strongly non-linear, while here we include here only a linear specification as our focus is on the role of unemployment shocks.

Table 3. Estimation results (coefficients)

	(1)	(2)
DSTI	0.057***	0.049***
	(0.000)	(0.000)
Interest rate	0.459**	0.502**
	(0.030)	(0.017)
Residual maturity	0.051***	0.051***
	(0.000)	(0.000)
Outstanding amount	0.052***	0.052***
	(0.001)	(0.001)
Foreign currency denomination = 1	-0.072***	-0.070***
	(0.000)	(0.000)
Age	-0.031***	-0.030***
	(0.000)	(0.000)
Income group = (p30-p60]	-0.342***	-0.480***
	(0.000)	(0.000)
Income group = (p60-p90]	-0.942***	-1.073***
	(0.000)	(0.000)
Income group >p90	-1.634***	-1.795***
	(0.000)	(0.000)
Transition to unemployment = 1	0.590***	0.319***
	(0.000)	(0.000)
Income group = (p30-p60] # Transition to unemployment = 1		0.498***
		(0.000)
Income group = (p60-p90] # Transition to unemployment = 1		0.542***
		(0.000)
Income group > p90 # Transition to unemployment = 1		0.938***
		(0.000)
Observations	6,893,415	6,893,415
Banks FE	Yes	Yes
County FE	Yes	Yes
Vintage FE	Yes	Yes
Origination FE	Yes	Yes
Pseudo R^2	0.0581	0.0592
AUROC	0.711	0.712

Note: P values are shown in brackets. ∗∗∗, ∗∗, and ∗ indicate statistical significance at the 1%, 5%, and 10% levels, respectively

[5] Keeping all other characteristics unchanged, a 10-percentage point increase in the DSTI ratio leads to a 0.25 percentage point increase in the probability of default for the average borrower.

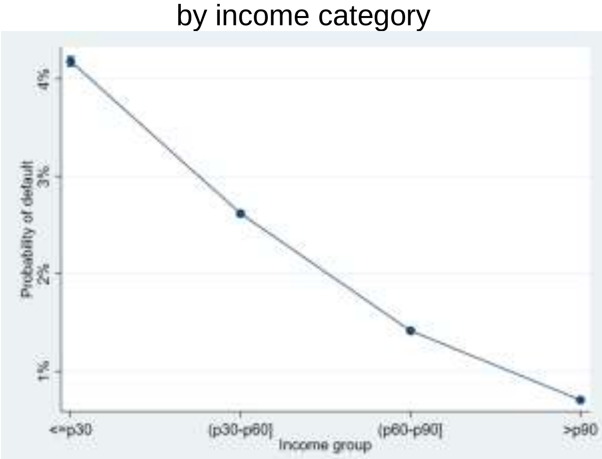
Turning to our variables of interest, we find that the probability of default decreases as income increases. Borrowers with incomes below the 30th percentile have a default probability which is twice the sample average (4.2% compared to 2.1% - Figure 3). In contrast, those with incomes between the 30th and the 60th percentile have a probability of default 2.6%, which is 30% greater compared to the sample average. This represents a 1.6 percentage point improvement.

Borrowers with incomes between the 60th and 90th percentiles have an average probability of default of 1.42%, which is 30% below the sample average. In the case of borrowers with incomes in the top decile, the average probability of default is 0.7%. Consequently, shifting from to the highest income distribution is equivalent to a 0.7 percentage point decrease in the probability of default.

Given that any increase in income at the lower end of the distribution allows borrowers to allocate a more funds towards subsistence expenses, we observe the most significant improvements at lower end of the distribution. On the other hand, shifting to a higher income category at the upper end of the distribution yields smaller improvements in default probability. This is because, at higher income levels, additional benefits of increased income diminish as debtors already have sufficient income to cover basic expenses and typically have a lower DSTI ratio.

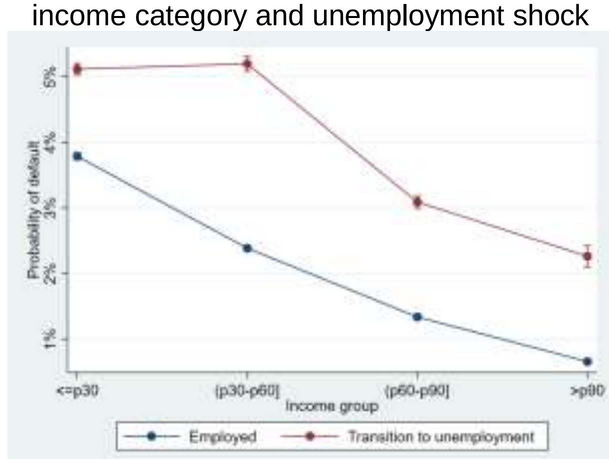
As expected, the coefficient for transition to unemployment is positive and statistically significant. On average, debtors which transition to the unemployment have a probability of default 3.8% compared to 1.9% for those which remain employed, respectively a doubling of the risk.

Figure 3: Average probability of default by income category



Source: Own calculations.

Figure 4: Average probability of default by income category and unemployment shock



Source: Own calculations.

Examining potential non-linear effects, we move to the specification in column (2) of Table 3 which shows the interaction terms between income category and transition to unemployment. For ease of interpretation, we focus our analysis on the average marginal effects presented in Figure 4. We find that debtors in the bottom 60th percentile of income who transition to unemployment experience a probability of default of approximately 5% (Figure 3). This suggests that borrowers in the lower income categories have limited savings and would struggle to cover basic living expenses, therefore deciding not to cover their monthly installments. Since these debtors represent about half of the sample, a significant portion of the portfolio is particularly vulnerable to unemployment shocks. In contrast, for debtors with incomes between the 60th and 90th percentiles, an unemployment shock raises the default probability to 3%. As for the top income decile, the impact is smaller, with the default probability increasing only to 2.25% after suffering an unemployment shock.

Robustness

We acknowledge that only a small share of debtors[6] may face transition to unemployment, while many may still face a negative income shock, while maintaining their employment status. This may be the case of a pay cut or a switch to a new job which is paid less after an unemployment spell. As show by McCarthy (2014), such developments can also have a significant impact on borrowers' ability to service their debt. As we cover the depth of the post Global Financial downturn in Romania, our sample period includes a period when many companies underwent restructurings and cyclical sectors, such as construction or manufacturing, increased redundancies or cut existing wages.

As a result, we also estimate an empirical specification which looks at the impact of income shocks on the probability of default. Similar to our baseline mode, the methodology employed is a logit model and is specified as follows:

$$y_{i,t} = \alpha + \beta' * Z_{i,t-1} + \delta' * L_{i,t-1} + \sum_{k=1}^{4} \sum_{j=1}^{4} \theta^{j}\, Income\ shock_{\,i,j,t-1} * Income\ shock_{k,t}$$
$$+ Bank\ FE + Origination\ FE + County\ FE + Vintage\ FE + \varepsilon_{i,t}$$

Where, the indices *i* and *t* represent borrower and time, respectively. As before, index *j* refers to income category, while index *k* to the income shock suffered by the debtor at time *t*. The income shock is determined by dividing the salaried income recorded at the Ministry of Finance at time *t* (the moment when default is observed) by the income declared at time *t-1*. It is crucial to note that borrowers who become unemployed are excluded from the robustness analysis, thereby we focus exclusively on those who remain employed during both periods. Four

[6] 9% of debtors in the sample experience a transition to unemployment at one point in time.

categories of income shocks are established: (i) a decrease greater than 50%, indicating a substantial reduction in income; (ii) a decrease ranging from 50% to 25%, reflecting a moderate decline in income; (iii) a change between -25% and +25%, signifying broadly stable income levels; and (iv) an increase exceeding 25%, indicating a significant improvement in earning capacity.

Table 4 presents the distribution of borrowers[7] by income shock categories. As expected, the majority of debtors (~60%) have had relatively stable incomes, with fluctuations between -25% and +25%. Interestingly, around a quarter of debtors have experienced income increases greater than 25% and their probability of default is slightly higher compared to those with stable incomes. Examining debtors who experienced a moderate negative income shock i.e. a reduction between -25% and -50%, we observe that only 5% of the sample falls into that category. Moreover, these debtors experience a significant increase in the average probability of default, showing that even moderate income shocks can have large consequences on payment capacity. Finally, those with an income reduction greater than -50% represent around 7% of the sample and have an average probability of default of 5.3%.

Borrowers who have stable incomes or experienced an increase in income are more likely to have higher incomes prior to the shock. This illustrates that illustrating that low-income borrowers are more susceptible to income volatility and negative impacts from economic cycles. Regarding other variables of interest (DSTI, foreign currency denomination, interest rate, residual maturity, age, outstanding amount), no significant differences are observed among the four groups.

Table 4. Mean values for main variables by income shock:

	(-100%, -50%]	(-50%, -25%]	(-25%, +25%]	>25%
Number of debtors	413,913	323,186	3,924,000	1,606,000
Probability of default	5.3%	3.2%	1.4%	1.7%
Income[1)]	261	283	328	302
Outstanding amount[1)]	3,458	3,374	3,682	3,360
FX	13.2%	13.6%	12.8%	10.8%
DSTI	29.4%	27.1%	25.9%	26.5%
Interest rate	13.2%	13.2%	12.7%	11.5%
Residual maturity[2)]	4.5	4.5	4.4	3.9
Age[2)]	40.8	41.0	42.0	41.2

Notes: [1)] amount in euro, [2)] years.

Source: Own calculations

[7] Excluding those who experienced an unemployment shock

The regression analysis shows a similar pattern. The specification in Table 5 includes all other borrower controls included in the baseline specification; however, they are not included in the table for brevity. Focusing on our coefficients of interest in column (1), the baseline coefficient, which is omitted relates to those with stable incomes. First of all, we observe that both negative income shock coefficients are negative and significant, with a greater magnitude for the larger shock, as expected. Accordingly, the average probability of default of debtor who experienced an income shock between (-50%, -25%] is 2,9%, as opposed to 1,5% for a debtor whose income is stable. Debtors with a significant income shock i.e. between -50% and -100%, but who remain employed, have an average probability of default of 4.4% after the income shock, which higher compared to the unemployment shock (3.8%).

On the other hand, the impact of positive income shocks is insignificant, showing the asymmetric nature. This is in line with O'Toole and Slaymaker (2021) who find that improvements in debt service do not impact borrowers' probability of default during crisis times.

However such analysis does not take into account that income shocks may have an asymmetric effect based on previous income level. As in our baseline analysis, we would expect low-income borrowers to be more sensitive to such shocks due to their higher level of indebtedness, lower savings and higher proportion of subsistence spending.

Table 5. Estimation results (coefficients)

	(1)	(2)
Income group = (p30-p60]	-0.416***	-0.629***
	(0.000)	(0.000)
Income group = (p60-p90]	-0.941***	-1.188***
	(0.000)	(0.000)
Income group >p90	-1.676***	-1.873***
	(0.000)	(0.000)
Δ Income = (-100%, -50%]	1.126***	0.566***
	(0.000)	(0.000)
Δ Income = (-50%, -25%]	0.693***	0.358***
	(0.000)	(0.000)
Δ Income >25%	0.004	-0.092***
	(0.628)	(0.000)
Income group = (p30-p60] # Δ Income = (-100%, -50%]		0.580***
		(0.000)
Income group = (p30-p60] # Δ Income = (-50%, -25%]		0.388***
		(0.000)
Income group = (p30-p60] # Δ Income >25%		0.063***
		(0.003)
Income group = (p60-p90] # Δ Income = (-100%, -50%]		0.867***
		(0.000)

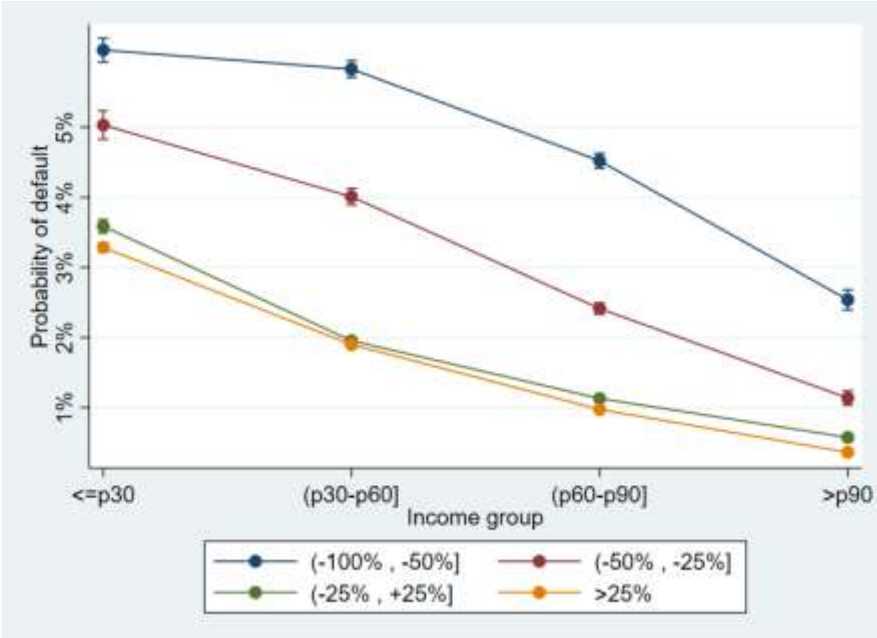
Table 5…

Income group = (p60-p90] # Δ Income = (-50%, -25%]		0.418*** (0.000)
Income group = (p60-p90] # Δ Income >25%		-0.059** (0.011)
Income group >p90 # Δ Income = (-100%, -50%]		0.948*** (0.000)
Income group >p90 # Δ Income = (-50%, -25%]		0.332*** (0.000)
Income group >p90 # Δ Income >25%		-0.374*** (0.000)
Observations	6,276,237	6,276,237
Borrower controls	Yes	Yes
Banks FE	Yes	Yes
County FE	Yes	Yes
Vintage FE	Yes	Yes
Origination FE	Yes	Yes
Pseudo R^2	0.0671	0.0690
AUROC	0.726	0.728

Given that the large number of coefficients makes their individual interpretation quite cumbersome, we will focus on the estimated probability of defaults by income categories shown in Figure 5.

First of all, we observe that, positive income shocks have a statistically significant effect on the probability of default, however the effect is extremely small, with a reduction in the probability of default of around 0.2 percentage points for most income categories, while for those with incomes between the 30th and the 60th percentile, the impact -0.05 percentage points. Second of all, moderately negative income shocks i.e. between -25% and -50%, have the strongest effect for debtors in the second tercile of the distribution: their probability of default increases by 2 percentage points (from 2% to 4%). For the poorest debtors, those in the bottom 30th percentile, the impact is slightly less powerful, as the increase is 1.45 percentage points. For debtors with incomes between the 60th and the 90th percentile, the increase amounts to 1.3 percentage points (from 1,1% to 2.4%). In the case of debtors in the top decile of the income distribution, the effect is only a 0.6 percentage point increase (from 0.55% to 1.15%). We observe a similar pattern for the largest negative income shock, with borrowers between the 30th and 60th percentile being the most affected, while those in bottom 30th percentile follow. The impact decreases for the two other upper income categories. This confirms our results in the baseline model, exemplifying the fragility of low-income borrowers to negative income shocks.

Figure 5: Average probability of default by
income category and income shock



Source: Own calculations.

CONCLUSIONS

Using granular debtor-level for Romania which spans seven years we analyze the impact of unemployment and income shocks on the probability of default of unsecured consumer loans. Despite their relative importance, the study of consumer loans has been ignored in the favor of mortgage loans. Given the significant importance of consumer loans granted by the banking sector in Romania, this gives us a great laboratory. We find that, on average, transitioning to unemployment leads to a doubling of the probability of default. Furthermore, we explore non-linear effects of unemployment shocks, demonstrating that higher income individuals have a higher ability to withstand an unemployment shock. Our results provide valuable insights for policy makers, credit institutions and researchers interested in credit risk assessment and financial stability.

Our work also offers important policy recommendations. In 2019, following the calibration exercise conducted by Nier et al. (2019), the National Bank of Romania introduced a 40% debt-service-to-income (DSTI) limit for RON-denominated loans and a 20% limit for foreign-currency-denominated loans. Our paper suggests that national authorities would benefit from introducing a stricter DSTI limit for low-income debtors, as they are more vulnerable to negative income shocks. While such a measure might have negative short-term consequences in terms of access to finance, these would be outweighed by improvements in the probability of default for these debtors. By ensuring a sustainable level of indebtedness, these debtors would be able to service their debt even in the face of a negative income shock, thereby maintaining a good credit history and ensuring their access to finance in the future.

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