

Are CESEE borrowers at risk? COVID-19 implications in a stress test analysis

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We simulate an increase in the unemployment rate to assess the impact of an income shock on the financial vulnerability of households in ten countries of Central, Eastern and Southeastern Europe (CESEE). According to our definition, a household is financially vulnerable when its debt service-to-income (DSTI) ratio is 40% or more. Using microdata from the 2019 fall wave of the OeNB Euro Survey allows us to calculate the share of vulnerable households in a consistent manner across countries. We use this indicator to analyze the response to various shock scenarios that are based on recent unemployment projections amid the COVID-19 pandemic. Given the unified microsimulation framework, we can provide a comparative assessment of the effects stemming from an increase in the unemployment rate on households' debt service capacity across the ten examined CESEE countries. Our results suggest that the share of vulnerable households increases almost linearly with a rise in the unemployment rate but to a very different extent across countries. We identify several factors for the observed variability, one being the amount of wage replacement rates. In countries where unemployment benefits are comparatively high, adverse effects can be mitigated to a significant degree.

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The COVID-19 pandemic has not only caused a global health crisis but also a worldwide economic crisis that is projected to be far deeper than the global financial crisis (IMF, 2020a). For the banking sector, the expected economic contraction constitutes the largest shock since the Great Depression. According to the recent global financial stability report released by the International Monetary Fund (IMF), banks entered the COVID-19 crisis with far higher capital ratios than in 2009 but the sheer size of the shock and the likely increase in defaults from firms and households may still pose substantial challenges to banks' profitability and capital positions (IMF, 2020b). From a financial stability viewpoint, it is of interest to know which and how many debtors will have a high risk of not being able to repay their loans as a result of the crisis in order to evaluate the adverse implications for the banking sector.

Against this background, this paper makes use of survey data to shed light on household debt in ten Central, Eastern and Southeastern European (CESEE) economies² from the perspective of the borrower. In particular, the aim is to assess how job losses due to the COVID-19 slump might impact on the debt service capacity of households. We hereby add three new aspects to the literature on stress testing CESEE households. First, by using unique data from the OeNB Euro Survey we are in the position to assess the financial situation of households in a time just

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² Bulgaria (BG), Czech Republic (CZ), Croatia (HR), Hungary (HU), Poland (PL), Romania (RO), Albania (AL), Bosnia and Herzegovina (BA), North Macedonia (MK), Republic of Serbia (RS).

before the COVID-19 crisis hit, namely in fall 2019. The latest available stress test exercise in a CESEE country was performed based on 2014 data (Bańbuła et al., 2016, for Poland).³ Second, we shed light on the responsiveness of indebted households to unemployment shocks in countries that so far have not been analyzed⁴. Finally, we conduct our stress test analysis based on a harmonized microlevel dataset and impose a unified simulation framework for a broad range of CESEE economies. This allows us to compare the magnitude of the resulting impacts across countries.

So far, the literature on stress test exercises to evaluate the vulnerability of CESEE households to adverse shocks is very rare and almost limited to single-country studies (Room and Merikull, 2017; Bańbuła et al., 2016; Galuščák et al., 2014; Sugawara and Zalduendo, 2011; Holló and Papp, 2007)⁵. We are aware of two papers that present findings on stress tests of indebted households for multiple countries. Ampudia et al. (2016) look at ten euro area countries, among them Slovakia as the only CESEE country, using 2010 data from the Household Finance and Consumption Survey (HFCS). Tiongson et al. (2010) stress test households' debt service capacity in seven countries (including three CESEE countries) based on EU Survey of Income and Living Conditions data from 2007 and Household Budget Survey data from 2006 or earlier. All the mentioned studies include scenarios in which the responsiveness of a debt burden indicator (measured in various ways) to an unemployment shock is assessed. Yet, it is hardly possible to compare the results of single-country studies with respect to the magnitude of the estimated impact. The reason is that the imposed shock scenarios (e.g. by which amount the unemployment rate is increased), the definition of the debt burden indicator, the data source and the time span used are very different. The estimated impacts in Ampudia et al. (2016) are not comparable either; though the authors look at multiple countries within a unified simulation framework, the countries are subject to different unemployment shocks⁶.

Therefore, in this paper we consider a scenario in which the unemployment rate is increased stepwise by the same amount in each country. This allows us to compare the magnitude of the adverse impact across countries and to identify those aspects that drive the countries' responsiveness to such shocks. Knowing these determinants can help assess effects from income shocks when microsimulation techniques or specific data are not at hand. However, according to recent unemployment rate projections, labor markets in CESEE countries will be hit to greatly varying degrees by the COVID-19 crisis (IMF, 2020a). In order to assess

³ A recent assessment of the impact of income shocks on households' debt service capacity in eight CESEE countries can be found in Albacete et al. (2020). As evaluating income shock effects is not the central issue in their paper, they do not perform a stress test exercise where macroeconomic shocks are mapped into a microsimulation framework. Instead, based on an ad hoc calculation using 2017 HFCS data, they show how vulnerabilities increase when the total monthly gross income of indebted households is reduced by 10% up to 50% (in steps of 10%).

⁴ To our knowledge, this includes Albania, Bosnia and Herzegovina, Bulgaria, North Macedonia and Romania.

⁵ For a broader literature review on the papers that use microlevel survey data to assess vulnerabilities in the household sector see Ampudia et al. (2016).

⁶ The income shock in Ampudia et al. (2016) is defined based on the variability of unemployment rates within each single country so that the probability of the occurrence of the shock is about the same for all countries. While this is a very reasonable approach that controls for the fact that countries' labor markets might be hit to a very different extent by an economic crisis, it has limitations when it comes to comparing the responsiveness of households to an unemployment shock across countries.

crisis implications, we include a scenario in which the unemployment rate is increased by individual amounts that correspond to the recent unemployment rate projections for the countries concerned.

Our paper is structured as follows. In section 1 we define the debt burden indicator and the underlying data source. Section 2 describes the simulation setup in detail. The results of our stress test exercise are then outlined in section 3. Finally, section 4 will conclude with a brief summary of the results and some remarks concerning the limitations of our simulation framework.

1 The metric: financially vulnerable households in CESEE

Before describing the debt burden indicator used as the metric in our stress test exercise, we want to devote some space to present the dataset and to discuss the limitations associated with it when analyzing household vulnerabilities.

1.1 Data

We use OeNB Euro Survey data⁷ to study the effects of job losses due to the COVID-19 crisis on the debt service capacity of households. The survey is conducted annually in ten CESEE countries in a harmonized way, where around 1,000 respondents are selected randomly and are interviewed (face to face) based on a standard questionnaire in the same reference period. To our knowledge, the OeNB Euro Survey has the highest coverage of CESEE economies (in terms of countries and population) of all data sources that are suitable for performing household stress test exercises in a consistent manner. Moreover, it makes it possible to assess the financial situation of households at a time just before the crisis hit, namely in fall 2019. Although the distribution of debt across households in a country does typically not change rapidly over time, it is very convenient to be able to estimate the adverse implications of projected job losses based on very recent data. This is especially true for periods where macroprudential policies have been implemented more frequently. The most recent example is Romania, where the median debt service-to-income (DSTI) ratio came down significantly in 2019 compared to 2017 according to OeNB Euro Survey data. This is most likely related to the fact that the National Bank of Romania introduced a DSTI limit of 40% in 2019, which was announced already in 2018. As the average loan maturity is around six years in Romania, borrower-based macroprudential measures can show an effect within quite a short period. Hence, the annual frequency of the OeNB Euro Survey is a big advantage in this respect.

Nevertheless, there are some shortcomings in the data, above all the lack of data concerning the wealth situation of households. Unfortunately, it is not possible to account for the financial buffers a household has due to the accumulation of wealth, so that our assessment of the debt service capacity of households relies solely on income streams. Likewise, we have no information on the total debt amount of each household in the 2019 data, which restricts our analysis to an assessment of the probability of default.⁸

⁷ General information regarding the OeNB Euro Survey (e.g. publications or technical details) can be obtained from the OeNB website at: <https://www.oenb.at/en/Monetary-Policy/Surveys/OeNB-Euro-Survey.html>

⁸ Based on the estimated probability of default, an extension would be to calculate the exposure at default, which is a standard measure of the risk to financial stability (see e.g. Albacete and Lindner, 2013).

As the main objective of the OeNB Euro Survey is to shed light on the financial situation of *individuals*, questions that relate to other household members are less frequent. In particular, socioeconomic characteristics (e.g. income and job situation) of all other household members are not covered. Hence, our micro-simulation allows only for one person per household to become unemployed. The impact from this restriction could change the vulnerability measure in both directions for households with more than one earner.

There is one dataset we are aware of that contains complete information on both households' wealth and income positions and on the socioeconomic characteristics of the individuals living in the household, namely the Household Finance and Consumption Survey (HFCS). The data derived from this survey are very well suited for performing stress test exercises across countries in a consistent manner (so far 20 European countries are covered), and HFCS data are much more comprehensive than the OeNB Euro Survey as far as the balance sheet information of the household is concerned. However, although the latest wave of the HFCS already covers eight CESEE economies⁹, the survey has not been conducted in seven out of the ten countries considered in this paper¹⁰. In terms of population, the HFCS represents 55% of the inhabitants living in the CESEE region compared to 88% covered by the OeNB Euro Survey.¹¹ Besides, the reference period of the latest HFCS wave is 2017 for most of the covered CESEE economies. Hence, given the different regional focus of both surveys and the different timing of the most recent survey waves, the HFCS is rather a complement than an alternative dataset for the purpose of this paper.

1.2 The vulnerability indicator

Several indicators have been used to assess over-indebtedness in the literature (see Bańbuła et al., 2016, for an overview). Most of the papers performing stress test exercises use either the DSTI ratio (Michelangeli and Pietrunti, 2014; Sugawara and Zalduendo, 2011) or the financial margin (Ampudia et al., 2016; Galuščák et al., 2014; Johansson and Persson, 2006) to measure the vulnerability of households. The main aim is to assess a household's repayment capacity in order to have a proxy for default risk. The financial margin is usually defined as the disposable income of the household minus basic living costs and loan installment payments. A household is typically classified as vulnerable if this indicator is negative. Ampudia et al. (2016) extend the definition of the financial margin by considering the amount of the household's liquid assets (available in the HFCS data). Using information on the wealth position certainly improves the measure of default risk as households that cannot service their debt out of their incomes are likely to withdraw from their savings to meet their debt obligations. At this point we want to highlight a recent paper by Albacete et al. (2020), who analyze a large set of household vulnerability indicators in seven CESEE countries based on the third wave of the HFCS. By looking at the liquid asset positions, they show that, in six

⁹ The CESEE countries that are covered in the third wave of the HFCS are Estonia, Latvia, Lithuania, Slovenia, Slovakia, Croatia, Poland and Hungary.

¹⁰ The overlapping country sample is Croatia, Poland and Hungary.

¹¹ The CESEE region, on which the comparison is based, comprises all countries included in the HFCS and in the OeNB Euro Survey, i.e. in total 15 economies. See footnotes 2 and 9 for the country samples of the respective surveys.

out of the eight CESEE economies, the median indebted household could service its debt for only less than two months when relying solely on its liquid assets. Only in Poland and Slovakia, the ratio of liquid assets to debt service payments is somewhat higher enabling the median household to service its debt for a longer period, i.e. five and six months, respectively. Overall, this points to little room for maneuver among indebted CESEE households in the presence of an income shock. Yet, as neither data on the wealth position nor on basic living costs¹² are available, we stick to the DSTI ratio as our metric.

The survey unit of the OeNB Euro Survey is the individual. However, some questions are posed to the respondent that concern the entire household, i.e. all people with whom the respondent is permanently living together. In the 2019 fall wave, respondents were asked to report the monthly loan installment payments of the household¹³. Further, a socioeconomic question that is included in the standard questionnaire of the OeNB Euro Survey provides information on the total monthly net income (after taxes) of the household. Based on these questions we construct the DSTI ratio as follows:

$$DSTI = \frac{\text{monthly loan installment payments}}{\text{monthly net income}} * 100.$$

In order to identify vulnerable households, we then need to set a threshold above which we classify households as having a high risk of not being able to repay their debt. While this is a rather ad hoc decision in general, there is some literature indicating that measures based on DSTI limits are relatively good indicators of financial stress (e.g. Albacete et al., 2018, and Bańbuła et al., 2016). Bańbuła et al. (2016), who were the first to assess the effectiveness of DSTI limits, use microdata from the study on household wealth in Poland conducted by the National Bank of Poland in cooperation with the Central Statistical Office in 2014 and find that – given a range of plausible preferences with regard to type I and type II errors – the optimal DSTI threshold lies between 30% and 40% for Polish data. In effect, thresholds are typically set within this range in the literature on household vulnerabilities (Michelangeli and Pietrunti, 2014, and Sugawara and Zalduendo, 2011). In some papers the effective threshold is somewhat higher than 40%, as the DSTI ratio is calculated based on gross income (e.g. Albacete et al., 2020, and Fessler et al., 2017).

Following the literature, we define households as vulnerable when their DSTI ratio is equal to or above 40%. The metric used in this paper is the share of vulnerable households in % of all indebted households (with debt service payments). In order to ensure that this indicator is representative for the target population, we

¹² Basic living expenses are proxied in several ways in the literature, mostly by using different out-of-sample sources that are very country specific (Bilston et al., 2015; Galuščák et al., 2014; Albacete and Fessler, 2010). In contrast, Ampudia et al. (2016) use an in-sample measure and define the basic living costs as 40% of the median household income in the relevant country. Hence, an alternative way of measuring household vulnerability based on OeNB Euro Survey data could be based on the financial margin using an ad hoc measure of basic living costs.

¹³ The question is worded in the following way: “Think of all members in your household that have loans. How much money does your household have to spend per month to service all these loans including interest and principal payments? If you do not know the exact amount, an approximate answer would also be helpful.” The answer categories are (1) amount per month, (2) my household does not have a loan, (3) don’t know and (4) no answer.

employ household weights using information on the region and the size of the household (i.e. number of household members). We will use this metric in our microsimulation and test its responsiveness to a range of income shocks. The results will reveal to which extent the share of vulnerable households increases (in percentage points) due to these shocks. Given that our focus is on evaluating changes in the vulnerability of households due to increases in the unemployment rate, we do not consider alternative vulnerability measures like household shares based on different DSTI thresholds or financial margins. This would be beyond the scope of this paper. Rather, we vary our model with respect to the ingredients that might influence the responsiveness of the vulnerability indicator to the crisis. Therefore, the paper pays special attention to covering a wide range of potential economic scenarios regarding the unemployment shock and its transmission. The different assumptions regarding these important factors are described in detail in the next section.

2 The stress test scenario

Having established a measure of household vulnerability, we will now outline the main ingredients that must be specified in order to set up the stress test exercise. In this section, we first define the unemployment shocks (2.1) and then discuss how a respondent is selected into unemployment by the model (2.2). Once the pool of new unemployed persons has been determined, it remains to define in which way the personal income of the selected persons is altered in order to recalculate the income of the household subject to the shock (2.3). Finally, we obtain the modified DSTI ratios and the new share of vulnerable households. After repeating the Monte Carlo simulation 1,000 times, we get the result by taking the mean value of the vulnerability indicator over all these draws. Our simulation design is static, i.e. we do not take into account second-round effects. Hence, households are not assumed to adjust their labor supply or financing decisions as a response to the unemployment shock.

2.1 The magnitude of the unemployment shock

Unemployment shocks are defined quite differently across the stress test literature. The simplest approach is to set the magnitude of the shock arbitrarily by increasing the unemployment rate in steps, mostly from 1 to 3 (up to 5) percentage points (e.g. Bilston et al., 2015; Galuščák et al., 2014; Albacete and Fessler, 2010; and Johansson and Persson, 2006). An alternative way is to define it in line with historical experiences of the countries of interest. Sugawara and Zalduendo (2011) for example uses the largest increase in the unemployment rate during a specified time period to define the shock for Croatian data (i.e. 6 percentage points between 2007 and 2010). A similar approach can be found in Bańbuła et al. (2016), who analyze Polish data, basing their unemployment rate scenario on the largest historical growth rate observed over the past 20 years (i.e. 2.7 percentage points). Another way to take into account historical developments is to define the magnitude of the shock based on the standard deviation of the observed unemployment rate (Room and Merikull, 2017, and Ampudia et al., 2016).

In this paper, the selection of the shock scenarios follows two objectives. First, we want to compare the responsiveness of the vulnerability indicator to shocks across countries, which requires a unified shock scenario rather than one where

historical developments of individual countries are considered. Therefore, in the first scenario we increase the unemployment rate in each country by 5 percentage points (in steps of 1 percentage point). At the same time, however, we aim to assess the implications from job losses due to the current crisis. This calls for a scenario with individual shocks as labor markets are supposed to be hit very differently across countries. According to the World Economic Outlook of October 2020 (IMF, 2020a) the unemployment rate is expected to increase by only 0.3 percentage points

in Albania but by 4.0 percentage points in Romania from 2019 to 2020 (see chart 1). Hence, in a second scenario, we will compare the countries' responsiveness to individual unemployment rate shocks, which are based on these projections. Of course, if the fight against the virus proves to be slower than assumed in the baseline scenario of the IMF, economic activity is expected to deteriorate further with more adverse implications for the labor market. Hence, the second scenario might soon be outdated. In this case, one could refer to the first scenario, which includes unemployment shocks of up to 5 percentage points and therefore provides us with results from unemployment paths far worse than projected by the IMF.

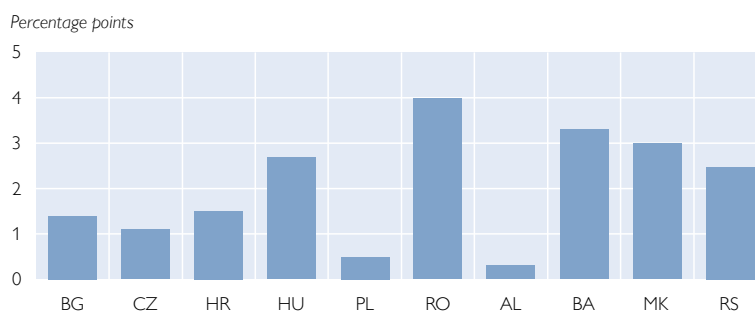
2.2 Selection into unemployment

Once the unemployment level is defined, we have to determine how individuals are selected into unemployment in our model. The simplest approach is to assign equal probabilities of becoming unemployed to all individuals (Johansson and Persson, 2006; Herrala and Kauko, 2007; Sugawara and Zaldueño, 2011; Holló and Papp, 2007). In a more advanced setup the selection is based on a probability model of unemployment taking into account that individuals with different personal characteristics have a different likelihood of becoming unemployed (Giordana and Ziegelmeyer, 2020; Room and Merikull, 2017; Bilston et al., 2015; Galuščák et al., 2014; and Albacete and Fessler, 2010).

In this paper we follow both approaches. While it is very likely that individuals are hit differently by an economic crisis in terms of job loss, the assignment of different probabilities to individuals is always based on past data. Hence, the unemployment shock will tend to affect individuals with characteristics that have historically been associated with a higher likelihood of being unemployed. Yet, these characteristics do not necessarily have to be good predictors for the COVID-19 crisis as, this time around, it might be certain sectors that are particularly affected by the economic downturn, like contact-intensive sectors, rendering individual characteristics less meaningful. Unfortunately, it is not possible to assign higher probabilities to individuals working in specific sectors as the corresponding information is not available in the OeNB Euro Survey. Therefore, we will stick to the common approach and estimate unemployment probabilities based on

Chart 1

Projected increase in the unemployment rate from 2019 to 2020



Source: IMF, October 2020 World Economic Outlook.

individual characteristics.¹⁴ However, in order to isolate the influence of assuming different probabilities on the simulation outcome, we also consider the less assumption-driven approach, where job loss is equally likely across individuals.

Heterogeneity in unemployment risk is estimated based on a probit model using data from the OeNB Euro Survey rounds of 2017 to 2019. We explain unemployment for each country separately by focusing on those respondents who are active on the labor market, i.e. employed and unemployed persons.¹⁵ The explanatory variables are the same for each country for comparison reasons and include individual and household characteristics (see e.g. Giordana and Ziegelmeier, 2020)¹⁶. Based on the estimated parameters, we predict the probability of becoming unemployed for each *employed* individual by varying the constant in the regression equation so that the mean probability (for the pool of employed persons) corresponds to the percentage share of employees transiting into unemployment. This share, let us call it x , is set so that the unemployment rate in the sample matches the shock scenario.¹⁷ Based on these estimated probabilities we set up the random selection process by following the approach in Albacete and Fessler (2010). We draw a random real number from a uniform distribution between zero and one for each employee. Whenever the individual probability is equal to or higher than this real number, we classify the working person as unemployed. Repeating this step 1,000 times results in different selections of individuals, where employees with higher unemployment probabilities will be overrepresented on average.

In the case of homogenous unemployment risk, the random selection is conducted in a quite similar way. The only difference is that the individual's probability is set to a value that is equal for all employees. This value corresponds to the targeted mean probability x defined above. We again assign a random real number drawn from a uniform distribution (between zero and one) to each individual and classify those employees as unemployed whose real number is below the probability value x .

2.3 Effects from a job loss on personal income

The 2019 fall wave of the OeNB Euro Survey provides information on each respondent's individual income as well as on the total income of each household. Hence, it is possible to reduce a household's income by the amount that is lost due

¹⁴ Note that some papers in the literature also model transitions from unemployment into employment (Galuščák et al., 2014; Baňbuła et al., 2016). In this paper, we assume that persons who are unemployed at the time of the survey stay unemployed after the shock.

¹⁵ Retired persons, students and other individuals outside the labor force (individuals on parental leave, unemployed people who do not seek a job) are excluded from our analysis.

¹⁶ The list of explanatory variables includes gender, education, (previous) profession (i.e. blue collar, white collar), age, the square root of age and the marital status of the respondent. Further we include the number of all household members and adults living in the household, the number of earners (excluding the respondent), homeownership, a dummy if the condition of the building the household lives in is poor and a dummy for big cities. As we estimate unemployment probabilities based on three waves, we also include year dummies.

¹⁷ We obtain x as follows: $x = \varepsilon / (1 - u_1)$ where ε is the magnitude of the shock ($\varepsilon = u_2 - u_1$), with u_1 being the actual unemployment rate and u_2 the unemployment rate after the shock (in the interval $[0, 1]$). If the magnitude of the shock is set to 2 percentage points and the actual unemployment rate is 7%, we calculate $x = 0.02 / (1 - 0.07) \approx 0.022$. Hence, 2.2% of all employed persons have to lose their jobs in order for the unemployment rate to increase by 2 percentage points.

to the income shock of the employee. We will look at two different scenarios. First, we assume that the shocked individual receives an unemployment benefit according to national regulations. In a second scenario, we assume that there are no unemployment benefits, i.e. the personal income of the respondent is set to zero. This scenario will serve as a benchmark in order to assess to which extent unemployment benefits can cushion households against the adverse effects from job losses on their vulnerability. There is one shortcoming with respect to the personal income data. It is not possible to distinguish between income from labor and other forms of income a respondent might receive.¹⁸ Hence, unemployment benefits are calculated based on the overall income of the respondent. Moreover, if the respondent does not receive unemployment benefits (second scenario), the overall amount of the income is set to zero. Hence, we might overestimate the negative impact resulting from a job loss.

The unemployment benefit in our stress test exercise corresponds to the amount of the net wage replacement rate according to national regulations. This rate is available from the OECD for six out of the ten countries under review and represents the share of net income from work that is maintained when people become unemployed. We complement this indicator for the remaining four countries by considering various sources (Council of Europe, ILO). Table 1 provides an overview of the wage replacement rate in the ten countries.

The OECD publishes several indicators of national replacement rates. We choose the replacement rate that applies to the average net wage of a job seeker who has been unemployed for 12 months.¹⁹ Note that the considered replacement rates are subject to a variety of assumptions reflecting the fact that national unemployment benefit regulations vary in terms of a lot of parameters: the employment history of the unemployed, contribution payments, minimum and maximum amounts received, benefit duration, household structure, etc. Hence, a single number reflecting the replacement rate is always a rough approximation of national regulations and can never be fully representative of the actual situation in a country. The assumptions behind the replacement rates offered by the OECD can be regarded as rather favorable for the unemployed person. Specifically, the replacement rates apply to a jobseeker aged 40 with an uninter-

Table 1

Replacement rate

	% of net average wage
BG	80.6
CZ	36.1
HR	47.9
HU	24.2
PL	49.5
RO	41.9
AL	30.5 ¹
BA	40.0
MK	50.0
RS	50.0

Source: OECD, Council of Europe, ILO.

¹ Please note that Albania provides a flat lump-sum payment of 11,000 lek, which corresponded to 30.5% of the net average wage in 2019.

¹⁸ The corresponding question in the OeNB Euro Survey says: "What is your personal total monthly income after taxes? If you cannot provide an exact amount, an approximate answer would also be helpful."

¹⁹ See <https://www.oecd.org/els/soc/methodology.pdf> for a detailed methodological description. As the OECD publishes replacement rates for different family types (e.g. single, couple with and without children, inactive spouse, etc.) we use a weighted average of these rates based on the country's household structure according to the OeNB Euro Survey. Note that we cannot use different replacement rates for different households when shocking a respondent's income, as the required information (e.g. spouse works full-time, is inactive, etc.) is not available in the OeNB Euro Survey.

rupted employment record since the age of 19 until the job loss. Moreover, they also include guaranteed minimum income benefits. Furthermore, if the receipt of benefits is subject to certain conditions, it is assumed that these are all met. Hence, the considered replacement rates in our microsimulation rather underestimate than exaggerate the income loss of the respondent.

In the second scenario, we assume that the respondent does not receive any unemployment benefits, i.e. the personal income is set to zero in the case of an unemployment shock. While in the first scenario the unemployment benefit conditions are rather favorable, this scenario represents the worst case of an income shock and therefore reflects the maximum negative impact on a household's vulnerability due to a job loss of the respondent²⁰. We want to highlight at this point that this scenario is not out of reach, as in most countries unemployment benefits are paid only up to a period of 12 months (or shorter) and are subject to fairly tough eligibility criteria (e.g. in North Macedonia a work record of 25 years is required in order to receive unemployment benefits for 12 months). Hence, this scenario can also be interpreted as a medium-term scenario assuming that labor market conditions do not improve after the eligibility for unemployment benefits ends.

After having defined all the important ingredients of the stress test model, it finally remains to reduce the household's income by the applicable amount and recalculate the DSTI ratios of the shocked respondents. The share of vulnerable households might then rise accordingly. Note that we abstract from the individual emergency measures implemented in the CESEE region (due to the COVID-19 pandemic) to protect borrowers through payment moratoria, as these reliefs are supposed to be temporary (Barisitz and Hildebrandt, 2020). Hence, our simulation results reflect the financial situation of households at a point in time when these measures will have expired. For a general discussion of changes in macroprudential measures in CESEE due to the COVID-19 pandemic, see also Eller et al. (2021).

3 Results

We first discuss the effects on the vulnerability indicator assuming an increase in the unemployment rate by 5 percentage points in order to compare the countries' responsiveness to a unified shock. By varying the scenario assumptions, we will see which role different unemployment benefit systems and heterogeneous unemployment risks in these countries play with respect to the outcome variable. In a second step, we will look at the increase in the vulnerability indicator when countries are hit by different unemployment shocks – set according to recent unemployment rate projections – to assess crisis implications.

3.1 Countries' responsiveness to a unified shock

In chart 2, we start out presenting the results of a 5-percentage point shock in the simplest setting, i.e. we assume that individuals have the same risk of becoming unemployed and receive no unemployment benefits. The blue part of the bar shows

²⁰ Overall, though, the scenarios are rather underestimations of the unemployment impact as our setting does not allow spouses and other household members to become unemployed (at the same time).

Chart 2

Share of vulnerable households after a 5-percentage point increase in the unemployment rate



Source: OeNB Euro Survey 2019.

us the actual share of vulnerable households in fall 2019²¹, which unveils a large heterogeneity across countries with respect to repayment risks. While in Hungary only 1% of all indebted households spend 40% or more of their incomes on debt service payments, in Romania nearly one-fourth of all indebted households have DSTI ratios equal to or above 40%. The comparably low share of vulnerable households in Hungary might be related to the debt restructuring measures taken by Hungary’s central bank in 2015 to deal with the high share of nonperforming loans back then (see also Riedl, 2019)²².

Based on the actual values in 2019, the dark red part of the bar shows to which extent the share of vulnerable households increases due to the unemployment shock. Again, we observe a large heterogeneity. The amount of the impact varies across countries but seems to be unrelated to the actual share of vulnerable households, i.e. we do not observe the largest impacts in countries with the largest actual shares of vulnerable households.

In chart 3, we depict the amount of the impact on a finer scale (dark red bar), which underlines the variability of countries’ responsiveness to the shock. The highest impact is observed in Bosnia (3.5 percentage points), where the increase is twice as high as in Romania (1.7 percentage points). This variability is driven by two very country-specific factors. First, the distribution of DSTI ratios across households determines how likely it is that the threshold of 40% will be exceeded after an unemployment shock. In countries where the share of households with DSTI ratios below but very near to 40% is high, the responsiveness to an unemployment shock is more pronounced. Second, the household structure has an important influence on the shock outcome. If the number of income earners in a household is high, income shocks can be absorbed much more easily. In Bosnia, where the shock responsiveness is highest, single-earner households are much more frequent than in the other nine CESEE countries.²³ Also, the share of households with DSTI ratios between 35% and 40% is highest in Bosnia.

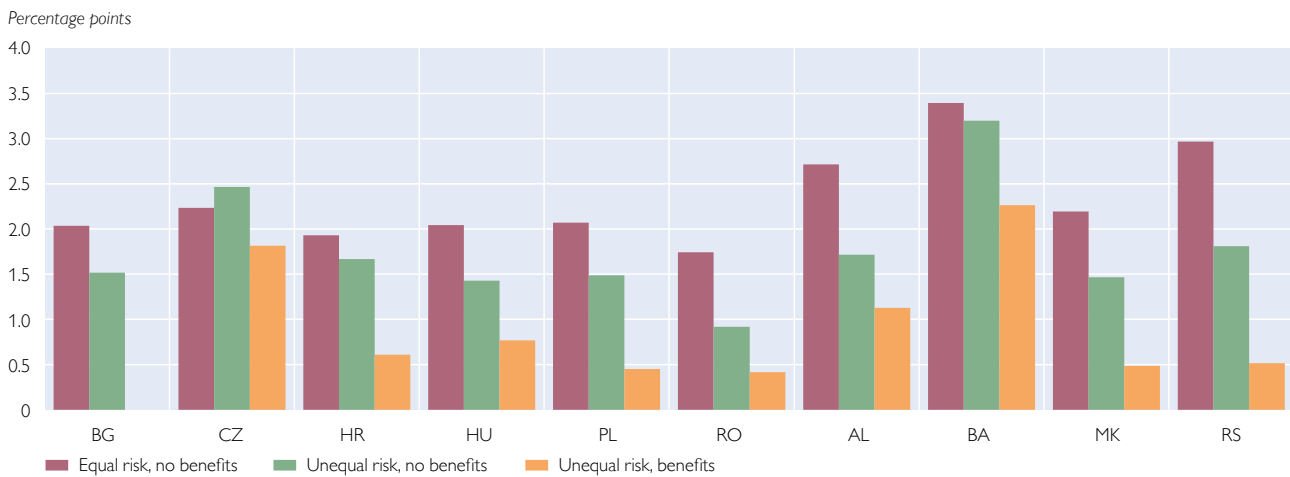
²¹ Note that the presented results all refer to households where the respondent is active on the labor market (see also section 2.2). However, the indicator does not change significantly when all households are considered and is therefore representative of the whole economy. See also table A1 in the annex for detailed descriptive statistics.

²² Riedl (2019) studies the relationship between household and loan characteristics and the level of DSTI ratios for the ten countries of interest. Note, however, that in general, explaining country heterogeneity would require considering a lot of factors that are potentially relevant for determining household vulnerability, like (macro-prudential) policies, macroeconomic developments or household and financial market characteristics. So far, the literature on the determinants of household vulnerabilities is virtually non-existent and mostly concentrated on single-country studies. Albacete and Lindner (2013), for example, study the relationship between household and loan characteristics and various vulnerability measures for Austria. Albacete et al. (2020) analyze how household characteristics influence the vulnerability measure across countries (Austria and various CESEE economies).

²³ The share of single-earner households amounts to 60% in Bosnia, 42% in Macedonia and 30% in Serbia. The country with the lowest share (12%) is Albania (OeNB Euro Survey 2017–2019).

Chart 3

5-percentage point shock: increase in the share of vulnerable households



Source: OeNB Euro Survey 2019.

In a next step, we vary the scenario by assigning different unemployment probabilities to respondents. The results are depicted by the green bars in chart 3. Comparing them to the outcome of the previous setting (dark red bars), we observe that in almost all countries the adverse impact is reduced when we assume heterogenous unemployment risk. This result reflects two opposing effects. First, in all countries except in the Czech Republic unemployment rates are lower for indebted households than for households with no debt. Hence, in most countries, the estimated unemployment probabilities are on average lower for respondents in indebted households. Therefore, fewer respondents from indebted households (compared to debt-free households) are selected into unemployment in the first place. This effect dampens the adverse impact resulting from the shock compared to the scenario where every individual was assigned an equal risk of losing their job. On the other hand, if out of the pool of indebted households those with the “bad characteristics” are selected first, the adverse impact of the shock could be reinforced. In the CESEE region, typically higher-educated, white-collar workers have lower DSTI levels and at the same time have a lower probability of becoming unemployed. Hence, assuming heterogenous unemployment risk implies that those respondents are picked first (out of the pool of indebted households) who have higher DSTI levels on average. Depending on which of the both effects dominates, this will either reinforce or dampen the adverse impact. In our setting, heterogenous unemployment risk has a dampening effect in almost all countries. This is in line with Bilston et al. (2015) and Tiongson et al. (2010) who find that assigning equal probabilities of unemployment to all individuals increases the effect of the unemployment rate shock on their vulnerability indicators.

Finally, we alter the stress test scenario by assigning unemployment benefits to individuals who lose their jobs while leaving the remaining assumptions unchanged. The orange bars in chart 3 represent the results from this scenario. While in all countries the adverse impact is reduced, we again observe large heterogeneities across countries. This is quite obviously related to the different national unemploy-

ment benefit regulations. When we recall the different wage replacement rates discussed in section 2.3 (see table 1), we can immediately see the correlation between the generosity of unemployment benefits and the shifts in the outcome compared to the previous setting (green bars). In Bulgaria for example, where unemployed persons receive a benefit of 80% of their net salary, the adverse impact from an unemployment shock vanishes completely. In contrast, in the Czech Republic, in Bosnia or in Albania, for example, where wage replacement rates are among the lowest in the region, the reduction of the adverse impact is least significant. Hence, our results argue in favor of generous allowances as they seem to significantly mitigate adverse outcomes.

Remaining in this scenario, chart 4 summarizes the results for unemployment rate shocks of 1 up to 5 percentage points. The colored parts in the bars represent the change in the share of vulnerable households after each percentage point increase in the unemployment rate. Thus, by summing up the individual effects, the height of the bars shows the overall impact from a 5-percentage point shock (orange bars in chart 3). For the reasons outlined before, the impact varies largely across countries. Interestingly though, the effect from the income shock seems to increase almost linearly with the unemployment rate in each country.

3.2 Different shock magnitudes based on recent unemployment projections

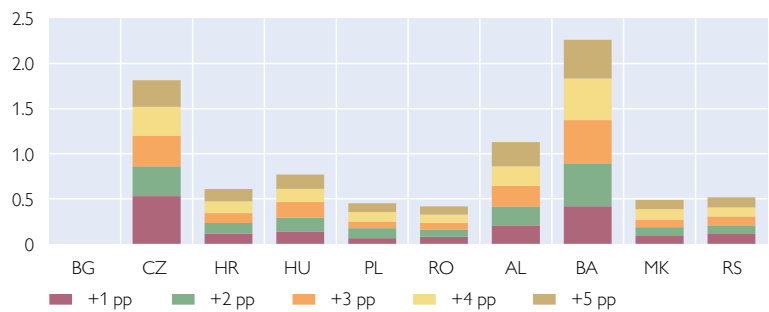
Finally, we present the results for the different stress test scenarios assuming that unemployment shocks are different across countries. As outlined in section 2.1, IMF projections serve as the macroeconomic input for the shock scenarios (see chart 1) designed to assess crisis implications. For projected increases in the unemployment rate of less than 1 percentage point (like in Poland or Albania) we impose a 1-percentage point shock, for the other countries we round to the nearest whole number.²⁴ Chart 6 summarizes the results of the individual unemployment shocks. Obviously, crisis implications regarding the vulnerability of households depend on which scenario we assess as the most realistic one. Generally, however, three things stand out. First, irrespectively of the stress test assumptions, the highest impacts can be observed in Bosnia, while Poland seems to be most resilient to income shocks. Second, our results indicate that the crisis will impact the various countries in the CESEE region to a very different extent. So far, we have observed a large country heterogeneity for income shocks of the same magnitude. Now that we assume different unemployment shocks – so that the probability of

Chart 4

Increase in the share of vulnerable households after unemployment shock

Scenario: unequal unemployment risk; positive unemployment benefits

Percentage points



Source: OeNB Euro Survey 2019.

²⁴ We assume a 1-percentage point shock for Albania, Poland, the Czech Republic and Bulgaria, a 2-percentage point shock for Croatia, a 3-percentage point shock for Bosnia and Herzegovina, Hungary, North Macedonia and Serbia and a 4-percentage point shock for Romania.

the occurrence of the shock is about the same for all countries – the ranking of the countries in terms of the size of the impact changes but country heterogeneity still remains very high. Finally, when we compare the estimated crisis impact with the initial (i.e. actual) share of vulnerable households in fall 2019 (see chart 5), we can classify the resulting increases as rather moderate in all countries. Of course, in Hungary, where the actual share of vulnerable households is very low, i.e. not even 1%, the share might double if the unemployment rate follows the projected path. However, the share in Hungary would remain the lowest in the CESEE region, even in terms of 2019 figures. In Romania and North Macedonia, where the share of vulnerable households is highest, the crisis impact amounts to less than one-tenth of the initial level.

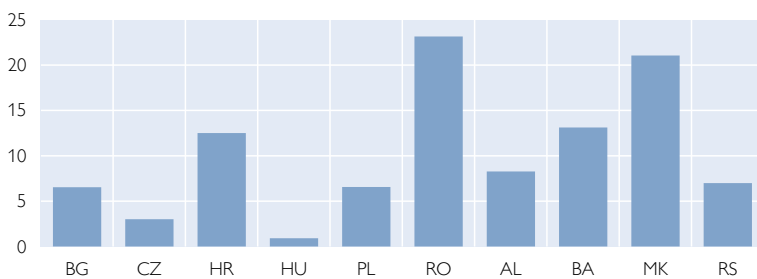
At first sight, the relatively modest impacts might seem surprising. However, given the fact that debt participation increases with net income in these countries (Riedl, 2019), indebted households have higher incomes in general, which makes them less vulnerable in case a household member becomes unemployed. (This argument of course does not hold for single-earner households.) Besides, in contrast to interest rate or exchange rate shocks, an unemployment shock hits only a small group of indebted households.

If we were to simulate an interest rate shock for example, it is very likely that we would observe much higher impacts across countries, as most household loans in these countries are variable interest rate loans (see e.g. Riedl, 2019). Also, in six out of the ten countries under review, a significant share of household debt is denominated in foreign currency. Hence, an exchange rate shock is likely to affect a much higher share of indebted households than an income shock.²⁵ A related argument can

Chart 5

Share of vulnerable households in fall 2019

% of all indebted households

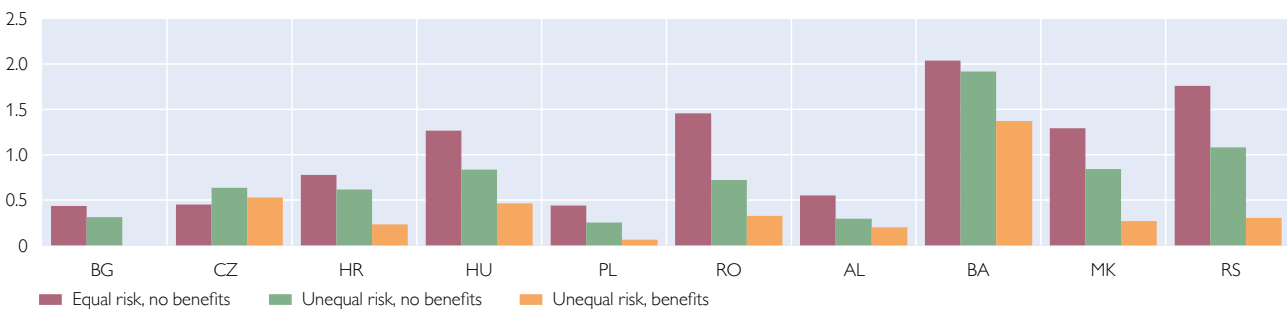


Source: OeNB Euro Survey 2019.

Chart 6

Shock based on unemployment projections: increase in the share of vulnerable households

Percentage points



Source: OeNB Euro Survey 2019.

²⁵ Given the lack of data we are not able to simulate these kinds of shocks within our framework. Fortunately, the risk of adverse interest rate or exchange rate shocks in these countries is so far rather low.

be found in Albacete and Fessler (2010), who show that the vulnerability of indebted Austrian homeowners is least sensitive to unemployment rate shocks compared to exchange rate and interest rate shocks.

Yet, the presented analysis has shown us by how much a projected income shock impacts on the probability of default. These results, however, must be seen against the background that information about households' total debt holdings did not enter the analysis (due to data limitations). Hence, we cannot estimate the proportion of the total debt that is held by vulnerable households and therefore cannot assess the exposure at default. Should the proportion of the total debt held by vulnerable households vary to a large extent across countries, the risks to financial stability could well be high in countries that have a rather low share of vulnerable households and vice versa. Extending the dataset in this respect would be very important for a deeper evaluation of the risks to financial stability.

4 Summary

We have analyzed the potential impacts from deteriorating labor markets on the financial vulnerability of households in ten CESEE countries. Based on a micro-simulation, we have shown that the effects from the projected increase in unemployment rates in 2020 will hit countries to a very different extent. Overall, though, compared to the initial (i.e. actual) share of vulnerable households in 2019, the impact from the COVID-19 crisis can be classified as rather moderate. This does not imply that CESEE borrowers are not at risk. On the contrary, we have seen that the share of vulnerable households is quite high in some countries. More than 20% of all indebted households in Romania and North Macedonia spend at least 40% of their disposable income to meet debt service payments. This share, however, will not increase significantly according to our stress test results. Even in our worst-case scenario, where we assumed unemployment rates that are higher than the most recent labor market projections (status: January 2021), the share of vulnerable households increases by a maximum of 3.5 percentage points (and by a maximum of around 2 percentage points in the two aforementioned countries). This is related to the fact that indebted households in general have higher incomes (compared to households without debt) as debt participation increases with income in these countries. Also, unemployment rate shocks only hit a relatively small group of indebted households compared to other shocks, like interest rate or exchange rate shocks. This is why effects from unemployment rate shocks are typically found to be modest in the literature.

We have also learned that countries' responsiveness is not only heterogeneous when we assume different unemployment shocks. Assuming income shocks of the same magnitude across countries has shown that the increase in the unemployment rate transmits almost linearly to an increase in the share of vulnerable households but to a very different extent across countries. The size of the impact varies with the distribution of DSTI ratios across households and with the household structure (number of earners per household). The adverse impact decreases in almost all countries under review when unemployment risk is assumed to be heterogeneous across individuals and when unemployment benefits are taken into account.

We have also discussed some data limitations we faced when performing our stress test analysis. Two of them are particularly relevant. First, we had to impose the restriction that only one individual per household can become unemployed.

The implications from this assumption are per se not assessable as this restriction could change the vulnerability indicator in both directions for all households with more than one earner. Hence, an interesting extension would be to model both scenarios to gauge whether the imposed restriction significantly alters the results. This could be done by using HFCS data, which so far cover three of the ten countries analyzed in this paper. Second, we have no information on households' overall debt amount. Hence, we cannot assess which proportion of the overall debt would effectively be at risk if all households classified as vulnerable in this paper were to default. This information, however, will be provided by the 2020 fall wave of the OeNB Euro Survey. Evaluating this data would certainly provide interesting insights concerning the adverse implications for the banking sector resulting from the COVID-19 crisis and would therefore be an interesting extension of this paper.

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Annex

Table A1

Descriptive statistics

	All respondents	Active respondents	DSTI ratio, all indebted households			DSTI ratio, indebted households, active respondents		
	Number of observations	Number of observations	Median, %	Households with DSTI≥40%, %	Number of observations	Median, %	Households with DSTI≥40%, %	Number of observations
BG	1,000	735	15.3	6.5	110	15.4	6.5	99
CZ	1,000	712	13.4	3.0	269	13.7	3.0	244
HR	1,031	690	18.8	12.5	225	18.8	12.5	182
HU	1,000	754	11.9	1.5	249	11.7	0.9	218
PL	1,016	637	14.3	6.6	69	14.3	6.6	69
RO	1,039	663	17.5	20.3	129	20.0	23.2	103
AL	1,000	785	21.4	8.5	290	21.5	8.3	272
BA	1,000	564	20.0	16.3	152	20.0	13.1	106
MK	1,006	578	21.3	22.3	182	21.1	21.1	132
RS	1,010	737	16.7	8.2	191	16.0	7.0	170

Source: OeNB Euro Survey 2019.

Note: In Poland, data was used only from interviews that were performed on paper due to an error in the question on loan installment payments in the computer-assisted interviews. This reduced DSTI-related observations from 119 to 69.

Active respondents are employed or unemployed persons. Retired persons, students and other individuals outside the labor force (parental leave, unemployed people who do not seek a job) are classified as inactive.