Climate Stress Test: The Impact of Carbon Price Shock on the Probability of Default in the Hungarian Banking System*

Bálint Várgedő

This study presents the methodology and results of a transition risk climate stress test carried out for credit institutions, focusing on the methodology of a sectoral module developed for the analysis. Using a sectoral network derived from an input-output table, the sectoral module distributes a price shock between activities with higher greenhouse gas emission intensity and the related sectors. Results suggest that the sectors with the largest exposure to transition are electricity and gas supply. The probability of default for these two sectors may increase by 1.5 to 2.3 percentage points compared to the baseline. The transition risks for various sectors are highly heterogeneous. Based on Monte Carlo simulations, the extent of the transition risks for Hungarian banks also varies significantly. The advantage of this methodology lies in its ability to estimate the magnitude of macroeconomic shocks and the transition differences across sectors, and its ease of integration into stress testing processes.

Journal of Economic Literature (JEL) codes: G21, G32, Q54

Keywords: climate stress test, transition risk

1. Introduction

In recent years, investigating the impact of climate change on the financial system has emerged as a new challenge for central banks, supervisors and market participants. Climate stress tests, as risk assessment tools, have again become the focus of inquiry due to the forward-looking nature of the problem, given the limited usability of methodologies based solely on historical data. Established by the Financial Stability Board, the *Task Force on Climate-related Financial Disclosures* (*TCFD 2017*) is among those recommending the use of scenario analysis and stress tests for companies and financial institutions.

---

* The papers in this issue contain the views of the authors which are not necessarily the same as the official views of the Magyar Nemzeti Bank.

Bálint Várgedő is an Analyst at the Sustainable Finance Department at the Magyar Nemzeti Bank and a PhD student at the Corvinus University of Budapest, Doctoral School of Business and Management. Email: vargedob@mnb.hu

The first version of the Hungarian manuscript was received on 1 August 2022.

DOI: https://doi.org/10.33893/FER.21.4.57

In my analysis, I quantify the effect exerted by a carbon price shock on the credit risk of companies operating in different sectors, in particular on the probability of default. In terms of specific policies, carbon pricing is one of the most effective and widespread instruments applied to reduce carbon emissions (*Nordhaus 1993*; *Stern 2007*). In the European Union, carbon pricing was implemented through the Emissions Trading System (EU ETS) mechanism. A number of EU countries (e.g. Austria) plan to reduce GHG emissions by means of a carbon tax in addition to the EU ETS. Income, whether from carbon taxes or carbon quotas, can be used in different areas of the central budgets, including support for the acceleration of the transition, the reduction of taxes on labour, or targeted transfers to those in need (*IMF 2022*). Based on IMF calculations, these budgetary options can significantly reduce macroeconomic losses in the short term. However, due to the risk focus of the analysis, I disregarded those options, as such measures (e.g. accelerating the transition) do not necessarily provide relief for the sectors most exposed to transition risks.

The carbon price increase was implemented via an increase in oil prices on the world market, using the Polaris macroeconomic model (*Soós et al. 2020*). In the case of Hungary, this amounts to an increase in the input cost of fossil fuels, just like an increase in carbon prices, as Hungary is a net energy importer, with 87 per cent of its oil consumption covered by imports (*Eurostat 2022a*). Subsequently, a sectoral model is used to propagate the macroeconomic shock across sectors. The model diffuses the primary shocks proportional to the carbon emission intensity of each sector through a sectoral network, derived from input-output tables of the sectors. Finally, the corporate probability of default (PD) model by *Horváth* (*2021*) is used to calibrate the magnitude of the probability of default specific to each sector.

The novelty of this study is the assessment and quantification of the short-term transition risks of the Hungarian banking sector, especially in respect of the probability of default for corporate loan portfolios. While there are exercises reported in the international literature that analyse the short-term transition risks of climate change (*Vermeulen et al. 2018*; *Guth et al. 2021*), often these methodologies cannot be implemented in Hungary due to lack of data and the use of non-public models. Nor did these analyses examine the possible extent of variation in the level of transition risks for different banks in the banking system. I use a Monte Carlo simulation to quantify this heterogeneity for seven major Hungarian banks. In addition, the study aims to ensure that the methodology it follows can subsequently be used by credit institutions in their own climate risk analyses.

Owing to its focus on risk, the study is primarily concerned with the risks and losses arising during the transition to a low-carbon economy. It is not intended to carry out cost-benefit analyses, since due to the nature of climate change this is only possible with the help of long-term analyses. The conclusions of such studies on Hungary suggest that the transition represents an opportunity for the Hungarian economy rather than a welfare loss (*Fazekas et al. 2021; Bokor 2022*).

In addition to climate change, the scenario examined in the study is also relevant in light of the high energy prices in 2022. The transition to a low-carbon economy and the elevated prices of fossil fuels both have a negative impact on a similar range of activities. Nevertheless, the study focuses on the assessment of transition risks.

Section 2 provides an overview of the relevant literature, with particular regard to the sectoral breakdown and time horizon. In *Section 3*, I briefly present the macroeconomic scenario, describe the methodology of the sectoral model used for the analysis and perform the calibration of the shocks. This is followed by the presentation of the data used. The results of the research are presented in *Section 4*, followed by a summary of the study in *Section 5*.

2. Overview of the literature

In recent years, a number of exercises have been elaborated internationally to model the effects of climate change on the financial system, mainly by financial supervisors and central banks. Stress tests of the bottom-up type, i.e. designed with the involvement of market participants, were carried out by both the French supervisory authority (*ACPR-BdF 2021*) and the Bank of England (*BoE 2019*). In addition, the European Central Bank (ECB) has also published its top-down exercise, conducted using mainly internal supervisory models (*Alogoskoufis et al. 2021*). One feature common to all three of these analyses is that they are long-term stress tests based on the scenarios of the Network of Central Banks and Supervisors for Greening the Financial System (NGFS). By contrast, the following three analyses, which are presented in more detail below, are more closely related to this study.

The Central Bank of Hungary (Magyar Nemzeti Bank, MNB) has produced its stress test using a 30-year time horizon to explore the long-term climate risks to the Hungarian banking system (*Bokor 2022*). The exercise focused on the evolution of non-performing loans (NPL rates) in different sectors. These rates were modelled in three climate scenarios: an orderly transition, a disorderly transition and a “hot world” trajectory. The results were dominated by transition risks in the case of the first two scenarios and by physical risks in the third. The sectoral economic trajectories were produced using the macroeconometric model Cambridge Econometrics E3ME, taking into account the governmental measures related to the narrative of each scenario (*Fazekas et al. 2021*). The surprising result of the modelling is that the Hungarian economy may follow a higher GDP trajectory in the event of an orderly transition. As regards credit risks, significant heterogeneity is observed in terms of the different sectors and the effects of the three scenarios.

In its short-term energy transition stress test for the Netherlands (*Vermeulen et al. 2018*), the Dutch central bank (DNB) examined the resilience of the financial system in four scenarios (policy, technology, both and loss of confidence). The stress test carried out in 2018 is relevant both on account of its pioneering nature and its methodological specificities related to the short time horizon. Having implemented the scenarios in the NiGEM macroeconomic model, the authors used their proprietary sectoral model to produce the sectoral impact of shocks. This was quantified by means of a so-called transition vulnerability factor, which – in parallel with the CAPM[1] beta – captures company/sector-specific sensitivity, but focuses on transition risk rather than market risk. A sector's level of transition vulnerability is based on the greenhouse gases (GHGs) emitted in the production of consumer goods manufactured by the sector. The GHG calculations for a final product in a sector are not limited to the emissions of the sector, but are based on the quantity emitted along the entire production chain. Thus, a carbon price shock is stronger for every member in the production chain of carbon-intensive goods. The GHG emissions are then prorated to the economic weight of the sector, and the resulting intensity indicators are normalised by the authors so that the average rate of the transition vulnerability factor is one. Losses incurred in the different scenarios were also quantified for the balance sheets of banks, insurers and pension funds. The results of the stress test suggest that the scenarios can cause "significant but manageable" losses to financial actors.

Another example of a short-term transition risk stress test is the exercise by the Austrian National Bank published in 2021 (*Guth et al. 2021*). In addition to measuring overall transition risks, the stress test seeks to assess the impact of the carbon tax reform that was introduced in Austria in 2021 on the financial system. The authors model the effect of two scenarios: an orderly carbon price rise trajectory, and a disorderly one. The modelling of the sectoral block used in the stress test is described in the supplement by *Königswieser et al.* (*2021*). Starting from the price-based input-output model, the modelling follows a series of steps to integrate the shock of carbon prices into the economic performance of the sectors. The complex methodology allows the authors to control, inter alia, for incomplete cost transfer, the adaptation of demand, as well as the second-round effects arising from the change in wages and employment. Based on the results of the stress test, the aggregate CET1 ratio of the Austrian banking sector may decrease by 0.7–2.7 percentage points, which represents a manageable effect according to the authors.

In addition to a study by *Bokor* (*2022*), several analyses have been published in the Hungarian literature in recent years with a focus on assessing the effects of climate change on financial markets and institutions. In her essay on the methodological considerations of climate stress tests, *Boros* (*2020*) highlights the specificities of

[1] Capital Asset Pricing Model

these exercises, the aforementioned time horizon issue and the importance of a sectoral breakdown. *Ritter* (*2022*) compared the high transition risk exposures of Hungarian credit institutions with the EU average. According to his results, Hungarian credit institutions were more exposed to the transition risks. *Bokor* (*2021*) proposed a simple carbon risk indicator that enables time-series analysis of the transition risks to the banking system as well as the identification of the institutions most exposed to the transition.

2.1. Sectoral breakdown

The use of macroeconomic models is a common practice in modelling the scenarios of traditional stress tests, assuming that the economic shock to companies affects individual sectors equally, the only difference being the sensitivity of companies. In contrast, the specificity of climate stress tests is that, as a result of the scenario narratives, the economic impacts are uneven across sectors. The most widespread scenario narrative implements the risks of the transition to a low-carbon economy through a carbon price or carbon tax hike. However, in addition to its macroeconomic effects, the rise in carbon prices weighs more heavily on certain activities involving high GHG emissions (e.g. coal-based electricity generation, steel production) than on other activities involving low emissions (including a significant part of services). Thus, in addition to the definition of macroeconomic paths, it is also essential to define economic indicators at the sector level, in order to obtain results that are more coherent with the scenario narrative. Apart from the economic sectors that are most sensitive to the shock postulated in the scenario narrative, the approach allows for the identification of credit institutions that finance these sectors more heavily and are consequently exposed to higher risks.

The first step in the common approach to producing sector-level economic indicators is to model the impact on aggregate indicators according to the results of a macroeconomic model, followed by the estimation of heterogeneous sectoral effects using a sectoral model. In their study comparing international practices of climate stress tests, *Baudino – Svoronos* (*2021*) use the term 'macroeconomic block' in reference to the step of quantifying climate risks in aggregated indicators at the macroeconomic level. Analogously, the breakdown of macroeconomic indicators into sectoral levels can be described as a sectoral block.

2.2. Long-term and short-term exercises

Based on international practices, two approaches appear to emerge in climate stress tests: short-term exercises and long-term exercises. Short-term stress tests typically cover periods of 2 to 3 to 5 years, while long-term stress tests typically quantify financial and economic impacts in scenarios with time horizons of 20–30 years. The specificities of climate stress tests and the time horizon issue, as well as the importance of a sectoral breakdown are highlighted in *Boros* (*2020*).

The unquestionable advantage of long-term analyses is that they can adequately address the physical risks of climate change, which are only expected to occur in the longer term. In addition, transition risks are expected to materialise fully over the horizon (*Baudino – Svoronos 2021*). In contrast, short-term exercises can handle a specific scenario, and thus they are only suitable for quantifying limited or special physical risks, which may realistically occur in the near future. Furthermore, it is not certain that transition risks will materialise over the time horizon being examined, but this poses a minor problem as they can be assumed to occur in the narrative of a severe but credible scenario.

However, in compiling the scenarios of long-term stress tests, a number of assumptions must be made, which may have a negative impact on the robustness of the results. For example, where the objective is to determine institution-level results in a supervisory top-down exercise, in the case of a 30 year scenario one frequently applied balance sheet assumption is that the composition will remain unchanged (static balance sheet assumption) and this may result in limited interpretability of the results. In addition, long-term scenarios are often based on complex economic models: in such cases, there is a possibility of using "black box" models, where the effects of different modelling decisions are difficult or impossible to distinguish. Moreover, if the assumptions are not properly documented, the explainability of the results will decrease, reducing the scope for use. *Stern et al.* (*2022*) expresses similar criticism for long-term integrated assessment models, on which stress tests are often based, highlighting very significant uncertainties in relation to physical risks. This uncertainty may stem from possible extreme risks, as well as from tipping points such as disintegration of the Greenland ice sheet.

However, with short-term stress tests, the difficulties listed above that need to be resolved are less relevant and easier to deal with. Their time horizons also fit better into the framework of business models, which are relatively short-term by climate change standards. In addition, they are better suited to established stress testing frameworks, as a result of which they can be modelled with lower resource requirements, and as such they can also serve as starting points for market participants.

In summary, long-term stress tests are more suitable for complex strategic decisions and cost-benefit analyses, as well as for examining the sustainability of financial institutions' business models. In contrast, short-term exercises can be useful for identifying institution-specific transition risks and as part of general micro-prudential supervision, and can provide guidance for market participants to manage their climate risks. Thus, the two approaches arguably complement rather than exclude each other.

3. Methodology

This Section describes the methodology of the study, detailing the framework of the macroeconomic scenario and the methodology of the sectoral block. First, I present the methodology of the primary effect of the transition shock, then the construction of a network that diffuses sectoral shocks, and with the help of these, the process of calculating the propagated shocks to each sector. Finally, I use the sectoral distribution of bank exposures and macroeconomic stress scenarios to calibrate PD effects on individual sectors.

3.1. Macroeconomic scenario

As short-term stress tests are primarily suitable for quantifying transition risks, those risks are also the focus of the stress test discussed in this study. In defining the scenario, the ease of implementation into widespread macroeconomic models has also been taken into account.

The narrative of the scenario is the large-scale introduction of carbon pricing, the most common policy instrument for the transition to a low-carbon economy. Carbon pricing is also recommended for decision-makers by *Nordhaus* (*1993*) and *Stern* (*2007*), being one of the tools best suited to curb GHG emissions, in addition to (and supporting, see *Acemoglu et al. 2012a*) technological development. In the scenario, a sudden and significant introduction is assumed, covering all sectors. The technical issue of the exact form of pricing, i.e. whether a carbon quota trading mechanism is introduced or a carbon tax is levied, is not of primary importance for modelling. Indeed, other emission abatement measures, such as restrictions on the production of internal combustion engines or the introduction of stricter energy criteria for newly built dwellings, can be perceived as carbon pricing by means of a carbon pricing equivalent, allowing any such measure to be matched by a carbon price increase which would have a similar abatement effect.

The economic stimulus of using the revenues from pricing is not part of the narrative of the scenario, similarly to the stress test by *Vermeulen et al.* (*2018*), and can therefore be considered conservative. The macroeconomic model integrates carbon prices through a 100 per cent increase in oil prices on the world market.

Both the scenario and the baseline were implemented using Polaris, a macroeconometric model by *Soós et al.* (*2020*). The advantage of the model is that it provides for an accurate fit with past behaviour patterns of the Hungarian economy, and that, as an error correction model, it takes into account both shorter and longer-term economic contexts. Polaris can be used to model a wide range of economic indicators at the national level.

In the scenario, several methodologies can be used to determine the extent of the shock. A common transition narrative is the introduction or increase of carbon prices, and the relevant literature may be useful in determining the magnitude of the carbon price increase required for the transition. For the policy scenario, the stress test by *Vermeulen et al.* (*2018*) modelled the effects of introducing a carbon price of 100 USD/tonne in the Dutch economy and financial system. In *Guth et al.* (*2021*), the effective carbon price in the Austrian economy increases gradually to 130 EUR in the orderly transition scenario over 5 years, and to 260 EUR in the disorderly transition scenario. Carbon prices may be conveniently implemented in macroeconomic models by means of oil price increases, a relatively common component of these models. According to a simple calculation by *Vermeulen et al.* (*2018*) burning a barrel of petroleum will produce 432 kg of CO_2 emissions, and thus an increase of 100 USD/tonne is equivalent to an oil price increase of 43.2 USD. Where gas, coal or energy prices are also included in the macroeconomic model, they can be calculated analogously by reference to the corresponding GHG intensities. To determine the magnitude of the shock, another common alternative in stress testing exercises is to rely on the extremes of the historical/modelled distribution of the shocked variable, for example, where the distribution function takes values of 95, 99 or 99.9 per cent. The doubling of the global oil price we are looking at corresponds to an oil price increase of 75 USD, which translates into an increase of 175 USD per tonne in the carbon price. From this perspective, the size of the modelled shock falls between the carbon price increases applied in the two exercises discussed above.

3.2. Sectoral block

In the sectoral model, sectoral heterogeneity is incorporated into the corporate probability of default through a sectoral deviation by deflecting PDs for macroeconomic stress paths by sector. Probabilities of default are defined as the chance of default as understood in banking, not the occurrence of bankruptcy or liquidation. When looking at the entire banking system, the deflections are neutral and the sum of the deflections (weighted by exposure) is zero. In other words, the aggregate results for the banking system are determined by the macroeconomic paths, with the deviations being responsible for the heterogeneity of the institutions financing different sectors with varying intensities. This allows us to identify institutions that are more sensitive to the given climate shock, but the magnitude of the overall impact will be consistent with the macroeconomic and PD models. In other words, the relationships observed in the past for economic and financial indicators will hold.

The modelling of the sectoral block can be divided into three parts: identifying the primary shock, modelling the propagation of shocks, and calibration.

3.2.1. Primary shock

The scenario narrative allows for the identification of the sectors that will be primarily affected by the shock. In the case of a carbon price increase, the extent of the primary shock can be well approximated by the GHG intensity of the sector, where the higher the carbon equivalent emissions per unit of added value, the more exposed the sector. The GHG intensity of each sector is available from the Eurostat database (*Eurostat 2022b*), broken down into 64 sectors.

The fundamentals of a company may be negatively impacted via multiple channels if it operates in a sector whose end product is subject to an extra tax. Where the company is unable to pass on to consumers all or nearly all of the higher costs due to the tax, its profitability may deteriorate sharply, accompanied by a fall in demand for the expensive product, depending on the price elasticity of the good. Thus, the lower volume sold in the new equilibrium represents lower sales for the company. According to the principles of economics, both effects increase the probability of default for the company.

3.2.2. Shock propagation

As can be seen from the above considerations, the shocks caused by the measures may have an impact on all actors in the production chain, which will apply to both cost transfer and falling demand. This requires modelling the relationships between sectors and exploring the network of economic activities. The basis for this is provided by the input-output table, which describes the production relations and supplier networks of sectors in the national economy. The role of the network of economic sectors has already been addressed by a number of researchers in relation to the propagation of idiosyncratic shocks to individual sectors (*Horvath 2000; Acemoglu et al. 2012b*). The methodology is thus partly based on those studies.

Before analysing the network of sectors, a formal definition of network needs to be provided. Each node in the network (i, j =1, 2, …n) is a sector of the economy, of which 64 are covered by the analysis (n=64). The edges of the network are determined by the strength of the link between the sectors. The network of economic sectors is best described by means of directed weighted edges, given that the individual sectors are suppliers and customers of one another (directed network), and even where they are interconnected, the strength of their links can be heterogeneous (weighted network).

The edge from sector i to sector j is determined by direct expenditure (Hungarian Central Statistical Office, *HCSO 2005*). This is the value of the goods used in production by sector j from the output of sector i, corresponding to item j in row i in the direct expenditure matrix T, $T[i, j]$. Normalising direct expenditures $T[i, j]$ by the total output (x_j) of sector j will produce technical coefficients (A_{ij}). The technical coefficients serve as the weighted edges of the network. The technical coefficient A_{ij} shows the number of units of output from sector *i* required for a single unit of output from sector *j*. The same applies with matrix operations, introducing matrix *A* ($A[i,j]=A_{ij}$) and the itemised inverse ($\frac{1}{x}[j]=\frac{1}{x_j}$) of total output vector *x*, along with identity matrix *I*, with *n* dimensions:

$$A = T \cdot I \cdot \frac{1}{x} \tag{1}$$

The resulting matrix *A* is therefore the adjacency matrix describing the edges of the network, whereby *A*[*i,j*] will be equivalent to the weight of the edge pointing from sector *i* to sector *j*. Note that in the case of technical coefficients (as with direct inputs), in production the output of sector *i* may be used to produce the final output of sector *i*. For example, the food industry may take input from the output of the same industry. This means that the diagonal of the adjacency matrix does not only contain zeros, i.e. there are self-loops.

The adjacency matrix shows the most important suppliers in each sector (the edges with the largest weights directed into the given sector) along with the most important recipients of the products of the given sector apart from end use (the edges with the largest weights directed out of the given sector). The sum of the former is the 'in' degree, while that of the latter is the 'out' degree, being two versions of degree resulting from the specific nature of directed networks. Degree is also a simple centrality indicator, where the higher the degree of a sector, the higher the number of sectors a shock to it can propagate to.

The adjacency matrix provides a more accurate picture of the propagation of an individual stress to a sector. Let $s_i^{(0)}$ indicate the initial individual shock to sector *i*. In the first round, according to the model it will spill over to sectors *j*=1, 2, …n to extent $s_j^{(1)} = s_i^{(0)} \cdot A_{ij}$. Analogously, shocks propagated in the first round will continue to propagate, in the second round also potentially from several nodes of the network $s_j^{(2)} = \sum_{i=1}^{n} s_i^{(1)} \cdot A_{ij}$. Note that the propagation of shocks can be well captured by means of matrix notation, even where several sectors are affected by the initial shock. Let vector *s* be introduced to indicate the initial shock, with item *i* being $s_i^{(0)}$. This allows formulating propagation in rounds 1, 2, ... k as follows:

$$\begin{gathered} s^{(1)} = A \cdot s \\ s^{(2)} = A \cdot s^{(1)} = A \cdot (A \cdot s) = A^2 \cdot s \\ \dots \\ s^{(k)} = A^k \cdot s \end{gathered} \tag{2}$$

Summarising the shocks in rounds 0, 1, 2, ... k, the following relationship is obtained for the sum of the shocks in the first k rounds $S^{(k)}$:

$$S^{(k)} = s + s^{(1)} + s^{(2)} + \cdots + s^{(k)} = s + A \cdot s + A^2 \cdot s + \cdots + A^k \cdot s \qquad (3)$$

Introducing the notation $S = \lim_{k\to\infty} S^{(k)}$ for the magnitude of a shock that has run its full course in the economic system, the sum on the right will accommodate the relationship known as the Neumann series, similar to the geometric series:[2]

$$S = \lim_{k\to\infty} S^{(k)} = \sum_{l=0}^{k} A^l \cdot s = (I - A)^{-1} \qquad (4)$$

The total shock thus obtained therefore shows the impact, in different parts of the economy, of a specific shock to a single sector of the economy or a subset of the sectors once it has propagated across sectors. It can be seen from the deduction that the shock will primarily impact the affected sectors as well as those in their immediate and indirect neighbourhoods, although the more indirect the relationship, the more moderate that impact will be. The method can also be used to identify the nodes of the network considered to be the most central based on its eigenvector centrality (*Anufriev – Panchenko 2015*). These sectors are the ones that will diffuse the shocks they receive to the greatest extent. A sector with lower eigenvector centrality will diffuse shocks less, which will consequently remain within the sector to a relatively higher extent.

The term $(I - A)^{-1}$ on the right side of the equation is the Leontief inverse commonly used in input-output modelling. Its other interpretation is how the demand shock per unit of a given industry affects the output of the whole economy as a result of the spill-over of the effects. Using the Leontief inverse thus allows us to quantify the full course of any initial shock for all sectors, providing for easy application in calculating multiple scenarios. Therefore, these properties meet the expectations for the sectoral block of a climate stress test.

There are several possible ways to integrate the sectoral results obtained into the scenario. One is that the sectoral block is used both to determine the extent of the shock to the macroeconomy and to model distribution across sectors. In this case, the macroeconomic block is also part of the sectoral block. An example is provided in *Guth et al.* (*2021*). The other option is that only the relative relevance of the sectors to one another is determined by the sector block, and the macro block is responsible for calibrating the average impact (for example, *Vermeulen et al. 2018*). In our methodology, we take the latter approach, so that the sectoral block is responsible only for the relative performance of the sectors.

[2] The eigenvalues of vector A must also satisfy the technical assumptions.

3.3. Calibration

The sectoral block was integrated into the stress testing process in accordance with the established stress testing methodology. The following two conditions can be used to clearly determine the PD changes in each sector, together with the desired coherence:

- Macroeconomic coherence: the average PD in the economy at the level is indicated by the macroeconomic paths of stress scenarios;
- Sectoral coherence: the relative size of *S* total shocks determines the PD increment of sector *i* compared to sector *j* relative to the baseline during the stress scenario.

The basic idea of the deduction is that for each sector, the total PD effect (dPD^i) is obtained as the sum of the PD effects of macroeconomic stress (dPD_{macro}) and the sectoral deflection ($dPD^i_{deflect}$). Macroeconomic stress is an effect of the difference between the stress path and the baseline, since the baseline does not involve any shock to the economy. Formally:

$$for\ \forall i\ sector\colon dPD_{macro} + dPD^i_{deflect} = dPD^i \tag{5}$$

dPD_{macro} can be estimated with the help of the point-in-time PD model, where $dPD^i_{deflect}$ is the variable sought and dPD^i is an indicator that is easy to interpret in economic terms, allowing sectoral results to be formulated. Once the two coherence constraints have been formalised and dPD_{macro} (not sector-dependent) has been estimated, the equation system can be solved for each sector. Introducing w^i to indicate the lending weight of sector *i*, the two constraints take the following form:

- Macroeconomic coherence:

$$\sum_i w_i\, dPD^i_{deflect} = 0$$

- Sectoral coherence:

$$for\ \forall i\ sector\colon\ \frac{dPD^i}{dPD^1} = \frac{dPD_{macro} + dPD^i_{deflect}}{dPD_{macro} + dPD^i_{deflect}} = \frac{S_i}{S_1}$$

The equations system is solved as follows:

$$for\ \forall i\ sector\colon\ dPD^i_{deflect} = dPD_{macro}\left(\frac{S_i}{\sum_j w_j\, S_j} - 1\right)$$
$$for\ \forall i\ sector\colon\ dPD^i = dPD_{macro}\frac{S_i}{\sum_j w_j\, S_j} \tag{6}$$

The result can be interpreted in such a way that the PD deflection of a given sector depends on the ratio of the total shock to the sector indicated by the macro model and the total shock to the average sector, and the magnitude of the deflection is calibrated by the macro PD shock. However, it follows from the definition that the constraints formulated for the total PD effect are still easier to interpret, deflection being only one component therein. The right-hand term of the equation, $\left(\frac{S_i}{\sum_j w_j S_j} - 1\right)$ is analogous to the transition vulnerability factor used in the Dutch stress test (*Vermeulen et al. 2018*).

The macroeconomic PD shock can be estimated by reference to the difference between the point-in-time PD model used in the stress test and the macroeconomic indicators. The macroeconomic variables included in the PD model in *Horváth* (*2021*) are disposable household income, along with the current period and lagged values of inflation and employment. The PD effect can be approximated linearly by using the average marginal effects (β_j) describing the sensitivity of the explanatory variables of the logit model. The macroeconomic PD effect only determines the amplitude of deflections, making minor inaccuracies due to linear approximation less problematic. Thus, only the deviation in macroeconomic variables is required. Per definition, dPD_{macro} is the PD effect resulting from the macroeconomic environment of the baseline and the stress path; consequently, the deviation sought will be obtained as the difference of the economic indicators between the predicted stress path (X_j^{stress}) and the baseline (X_j^{base}).

$$dPD_{macro} = \beta_1(X_1^{stress} - X_1^{base}) + \cdots + \beta_k(X_k^{stress} - X_k^{base}) \tag{7}$$

Table 1
Average partial probability coefficients of the significant macroeconomic variables in the *Horváth PD model*

Dependent variable: 'Default'	
Households' disposable income (dlnhhinc)	–0.1108*** (0.0229)
Inflation (dcpi)	–0.0008* (0.0004)
Employment lagged by one year (l1_demp)	–0.00005*** (0.0000)
Households' income lagged by one year (l1_dlnhhinc)	–0.1007*** (0.0259)
Imports lagged by one year (l1_dlnim)	0.0211*** (0.0001)

*Note: *p<0.1; **p<0.01; ***p<0.001; robust standard errors in brackets.*
Source: Horváth (2021): Table 2

The significant macroeconomic variables and their coefficients used in the corporate PD model are presented in *Table 1*. The default definition used in the model was defined on the basis of the banking analyses of eight large Hungarian banks, which were collected by the MNB as part of its supervisory activities between 2007 and 2017.

In this way, instead of liquidation procedures and other approximation techniques, the model is based on real bank default events, which were included in the database in annual terms at the customer level. The exact form of the explanatory variables of the model and the interpretation of the coefficients permit the following to be stated: *"The results show that a 1 per cent decline in household income (dlnhhinc) raises the probability of default by 11 basis points in the year of the shock, and – as a carry-over effect – nearly to the same degree in the following year as well. The labour market exerts its impact on the default rate through the change taking place in private sector employment* (*100,000 job losers raise the probability of bankruptcy by 50 basis points within a year*)*. In addition to all of these factors, the role of the inflation environment is another determinant."* (*Horváth 2021:p. 58*)

Thus, the identification of primary shocks can be performed by Leontief inverse after modelling the shocks spreading to the economic sectors, and subsequently PD deflections per sector can be generated, using the macroeconomic impact estimated during calibration. Adding these to the results of the point-in-time PD model produces PD values that reflect macroeconomic fundamentals along with the fundamentals of both the sector and the company.

3.4. Data

The range of data used is essentially based on three different sources. One is GHG intensity broken down into 64 NACE 2-digit sectors as reported in *Eurostat* (*2022b*), which determines the extent of the primary shock to companies in the sectors. In the rest of the study, I refer to NACE 2-digit sectors as subsectors and NACE 1-digit sectors as main sectors. For the establishment of the sectoral network, an input-output table is also incorporated; this is managed and updated at 5-year intervals by the HCSO. For the calibration and the quantification of the effects on bank losses, the exposure data from the MNB's HITREG database are required. In the analysis, I used the exposures of seven major Hungarian banks, which I constructed on the basis of the 'gross book value' field in HITREG. The exposure data were aggregated by sector in the calculation of deflections, more granularly in simulations, broken down by borrower and credit institution.

4. Results

4.1. Macroeconomic scenario results

Table 2 shows the impact on the macroeconomic indicators of the carbon price increase scenario implemented through an oil price increase using the Polaris model. GDP growth in the scenario falls significantly short of the baseline, especially in 2022, when the shortfall is more than one percentage point. This year also sees the largest shortfall compared to the baseline in terms of inflation, imports and household incomes. For the most part, the effect of labour market developments will be felt by 2023. Overall, however, the scenario is not extreme, and the results outline a less severe scenario compared to the regular stress path of the MNB.

Table 2
Deviation in macroeconomic indicators between the stress path and the baseline over a three-year time horizon

	GDP	Unemployment rate	Inflation	Disposable household income	Private sector employment	Imports
	annual change (%)	*annual average (%)*	*annual average (%)*	*annual change (%)*	*annual change (%)*	*annual change (%)*
2021	–0.40	0.03	1.42	–1.42	–0.04	–0.52
2022	–1.23	0.32	2.28	–2.59	–0.42	–1.82
2023	–0.79	0.49	0.60	–1.27	–0.23	–0.83

Note: The table shows the percentage differences between GDP, disposable household income, employment in the private sector and the annual growth rate of imports. For the unemployment rate and inflation, percentage differences between annual averages are shown.

The PD deviations estimated from the deviations of the stressed macroeconomic paths are reported with their components in *Table 3*. In the carbon price scenario, the estimated probability of default increases by 24 and 39 basis points in the second and third years, respectively; in the first year, the effect is close to zero.

Therefore, the probability of default appears to increase gradually over the time horizon. One reason is that in the economic indicators the largest deviation from the baseline occurs in the second year. On the other hand, in the estimated PD model emphasis is placed on the historical values of the economic variables. Thus, in the third year, spill-over effects from the previous year also increase the estimated PD difference. The higher PD in the stress path is mainly due to a decrease in disposable household income (its value lagged by one year). The effect is dampened by the rise in inflation, which, according to the model, reduces the probability of default for companies. The fall in employment only leads to a significant increase in the default rate at the end of the time horizon, and even then its extent falls short of the increase in disposable income.

Table 3
PD effects of economic indicators compared to the baseline

	Disposable household income	Inflation	Imports	Disposable household income lag	Private sector employment lag	Total PD effect
	percentage point					
2021	0.16	–0.11	0.00	0.00	0.00	0.04
2022	0.29	–0.18	–0.01	0.14	0.01	0.24
2023	0.14	–0.05	–0.04	0.26	0.07	0.39

Note: PD effects of economic indicators implied by the macroeconomic scenario, expressed in percentage points, and the overall PD effect in different years.

According to the methodology, in the case of a carbon price shock, the macroeconomic PD shock used for calibration is 4, 24 and 39 basis points, respectively, over the three years of the time horizon. In order to calculate the shocks to each sector, it is necessary to calculate the total shocks that affect them and propagate across the network of sectors.

4.2. Sectoral shocks

The GHG intensities of the individual sectors are shown in *Table 4*. As in the rest of the study, for the sake of transparency, I presented the results averaged by main sectors of the economy; accordingly, the figures show the results broken down by 21 main sectors, instead of the 64 subsectors. In the calculation of the average, I used lending to individual sectors as a weight. In this way, the result for the given main sector is not biased by subsectors less relevant from a lending perspective. Obviously, only the ratio of the sectors to one another matters when determining the primary shocks. It can be identified that certain parts of the economy are more affected by the measure. Sectors primarily affected on account of their high GHG intensity include Sector D, which also involves electricity and gas supply, Sector B (mining), and Sector E (operation of utilities).

Table 4
Sectors of the national economy and their GHG intensity

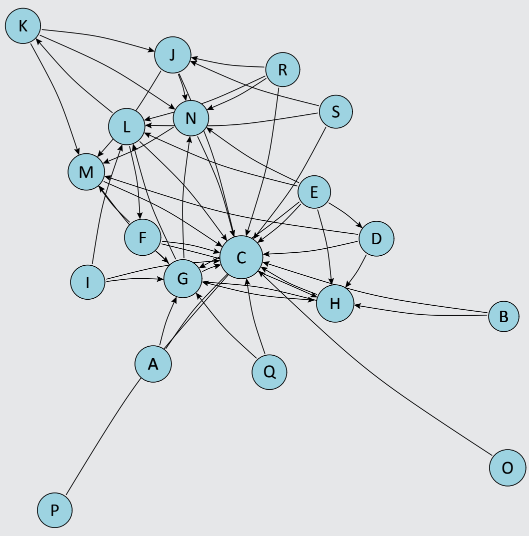
Economic sector	GHG intensity (g/EUR)
Agriculture, forestry, fishing (A)	1,987.7
Mining and quarrying (B)	1,624.3
Manufacturing (C)	471.6
Electricity, gas, steam and air conditioning supply (D)	5,789.3
Water supply, sewerage collection and treatment, waste management and remediation activities (E)	3,889.0
Construction industry (f)	166.0
Trade and repair of vehicles (G)	182.6
Transportation and storage (H)	902.2
Accommodation and food service activities (I)	81.9
Information and communication (J)	49.0
Financial and insurance activities (K)	42.2
Real estate activities (L)	38.9
Professional, scientific and technical activities (M)	46.6
Administrative and support service activities (N)	175.1
Public administration and defence, compulsory social security (O)	80.3
Education (P)	39.3
Human health and social work activities (Q)	66.7
Arts, entertainment and recreation (R)	42.3
Other services (S)	49.9
Activities of households as employers of domestic personnel; goods- and service-producing activities of private households for own use (T)	35.7
Extraterritorial organisation (U)	

Note: The intensity indicator is constructed on the basis of the value added.
Source: Eurostat (2022b); HCSO

Figure 1 is a representation of the network constructed as per *Subsection 3.2.*2, using the matrix of technical coefficients produced based on the method described in the same subsection. The figure shows the network that, according to the model, propagates the initial shock received by one or several sectors in the network to the sectors linked to them. The adjacency matrix of the network is the matrix of the technical coefficients. Thus, the size of the edge from node *i* to node *j* is equal to the number of units of output *i* required to produce a unit of good *j*, that is, the amount of shock to sector *j* caused by a shock to sector *i*. For the sake of transparency, the only edges shown are those assigned with weights of more than 0.03, implying relatively strong shock transmission. For similar reasons, instead of the more granular sectoral breakdown (subsector), the network of main sectors is displayed, but the precise calculations were made using the more detailed breakdown.

Among the national economy sectors of primary importance for the analysis, in the first step shocks are transmitted by Sector D mainly to Sector C (Manufacturing) and Sector H (Transportation, warehousing). Sector B also has strong links to Sector H and Sector M (Professional, scientific and technical activities), while shocks are transmitted from Sector E to nodes D, C and L (Real estate activities).

Figure 1
Sectoral network of the Hungarian economy



Note: Representation of the network of Hungarian national economy sectors constructed on the basis of technical coefficients. The nodes indicate the individual national economy sectors, and the directed edges indicate the links between them, weighted by the magnitude of the technical coefficients. Self-loops and edges assigned with technical coefficients below 0.03 are not shown. The size of each node is proportional to the total output of that sector. The location of network nodes was determined according to the Fruchterman–Reingold algorithm. The calculation of the technical coefficients was carried out as described in the text, on the basis of the HCSO's symmetrical entity-to-entity input-output table for 2015.

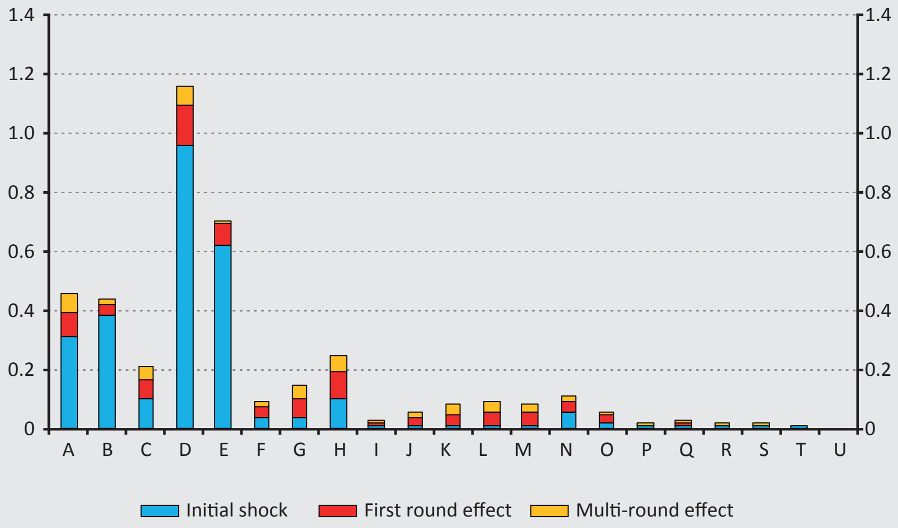
Source: Calculated based on HCSO data

The initial shocks are shown in *Figure 2*, along with the shocks propagated across the network, both after the first propagation round and the equilibrium total shock. Obviously, as a result of the propagation, the shock after the first round is always greater than the initial shock, and then a higher value will be shown by the shock that has run its full course. It can also be observed that network propagation distributes the shocks, and the initially concentrated shocks show a slightly more homogeneous picture having run their course, although the extent of the shock varies considerably across sectors.

Even after propagation in the first and subsequent rounds, the largest shocks are still received by Sectors A, B, D and E, which were originally affected the most. Although initially not affected significantly, Sector H suffers significant shocks from the related sectors. The same applies to Sectors G and C. Despite their low GHG emissions, Sectors L, K (Financial and insurance activities) and M also become affected as a result of propagation, but not strongly.

Whether and how national economy sectors are affected in relation to one another in the context of a PD increase is determined by the total equilibrium shocks reviewed. The PD effect sought can be determined by reference to the exposure distribution of bank portfolios, broken down by national economy sector.

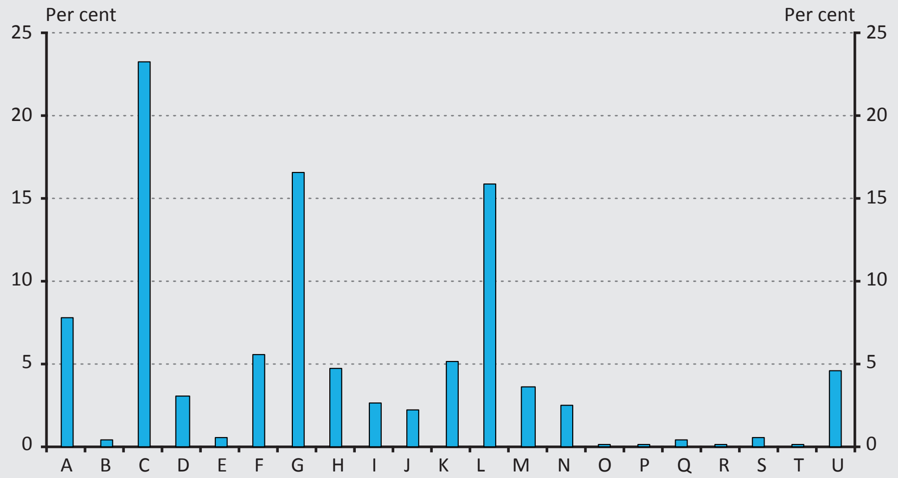
Figure 2
Result of shock propagation in the sectoral network by national economy sector



Note: Information is carried by the relative magnitude of the shocks.

The exposures of Hungarian credit institutions to sectors of the national economy are shown in *Figure 3*. Based on exposure, about one quarter of lending is directed to the manufacturing industry (C), but trade (G) and real estate (L) each also account for more than 15 per cent of the portfolio. Loans to agriculture account for 7.8 per cent of the total, with Sector D representing a mere 3 per cent. The lending ratio of Sector B, which has a high GHG intensity, is also very low at 0.4 per cent.

Figure 3
Distribution of bank credit exposures broken down by national economy sectors in mid-2021

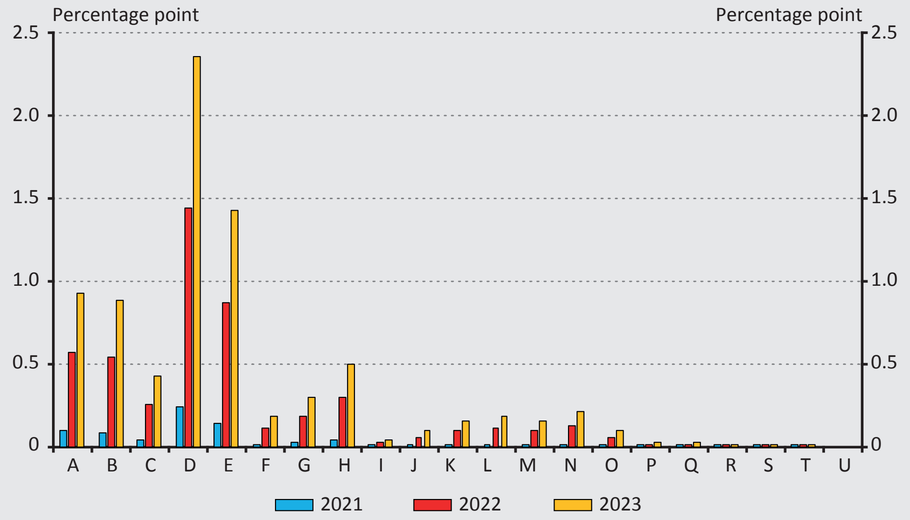


Note: Calculated on gross book value
Source: MNB: HITREG

The PD impact of climate shocks for each sector can be calculated as outlined in *Section 3* by means of the estimated macroeconomic PD effect, the relative size of the total shocks to sectors, and the distribution of exposures (*Figure 4*). The sector-specific PD effect varies from year to year, as the PD effect estimated for each year also varies. As a result, differences between the individual years are only found in this calibration term, and the extent to which the sectors are affected is stable over the years. In line with the evolution of the macroeconomic PD effect over time, the PD effect increases year on year over the time horizon for both scenarios.

The largest PD effect in the case of the carbon scenario is the PD deviation of Sector D from the baseline in 2023, by 2.35 percentage points. The value calculated for 2022 is 1.44 percentage points. A similar value is 1.42 percentage point for Sector E in 2023. In that year, Sectors A and B both suffer a significant PD effect according to the modelling, at slightly below 1 percentage point. The PD effect for Sector H peaks at 0.5 percentage points in 2023, followed by Sector C at 0.42 percentage points. It can be said that a number of national economy sectors are not affected by the shock even through spill-over effects, and consequently no meaningful PD effect is produced in the modelled scenarios. These are the activities in Sectors I (Accommodation), P (Education), Q (Health) and R (Arts).

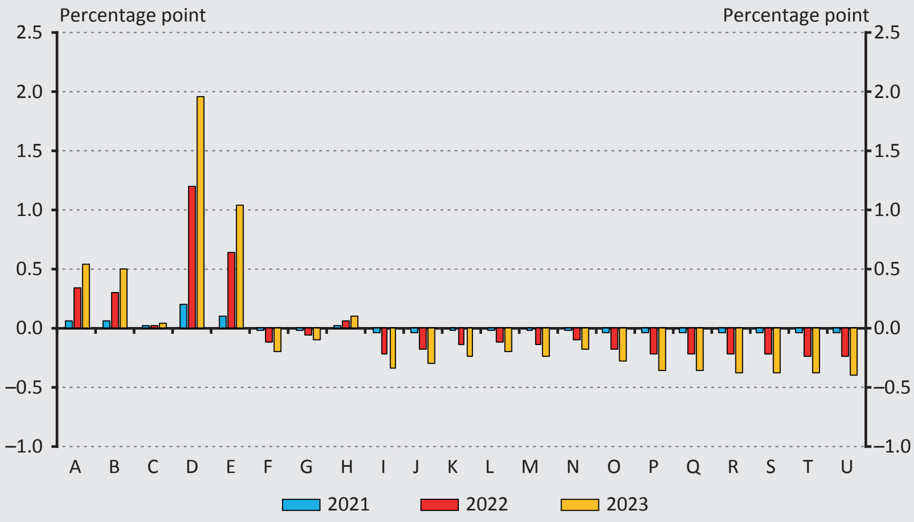
Figure 4
Modelled PD increment of the stress scenario compared to the baseline, by national economy sector



Aggregation at the level of main sectors as shown in the figures has benefits in terms of interpretability and transparency, but raises the question of how much granular information it conceals about the heterogeneity of the subsectors. The answer to this question can be given by examining the variance of PD effects. The total variance can be disaggregated into the variance within each main sector and the variance across main sector averages. According to my calculations, the variance occurring within national economy main sectors accounts for 21.9 per cent of the total variance, with the remaining 78.1 per cent resulting from the difference between the main sectors. Granular sectoral analyses can therefore lead to materially more accurate results in practice. Consequently, where possible, a granular breakdown should be used when analysing transition risks.

Also of interest from a modelling perspective is the extent of PD deflections, which can be determined as outlined in *Section 3*. PD deflections help determine the extent to which the results of a standard corporate PD model based on macroeconomic variables in each sector need to be increased or decreased in order to obtain results that are consistent with the scenario. PD deflections are shown in *Figure 5*. According to the results of the carbon price scenario, the PD results of Sectors A, B, D, E and H are to be increased. According to the modelling, the remaining sectors are less affected by the carbon price increase than would otherwise be inferred from the macroeconomic indicators.

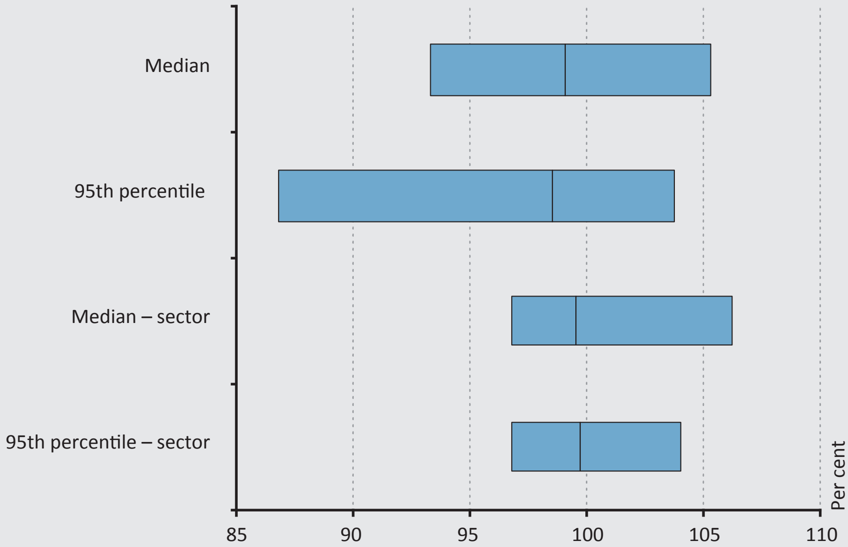
Figure 5
Extent of the modelled PD deflections of national economy sectors



Using the deflections, a Monte Carlo simulation can be produced for the corporate loan portfolios of banks, assessing the impact of deflections on banks. This allows us to identify the banks whose credit risk is negatively affected by the sectoral heterogeneity of transition risks. For simulation purposes, probability of default was assumed to be homogeneous within each sector, whereby the probabilities specifically represent the risk differences resulting from the sectoral composition of bank portfolios. The simulations were based on the corporate credit exposures of seven Hungarian banks participating in the exercise. For simulation purposes, all loans of a company with a given bank are assumed to become non-performing or remain performing collectively. Thanks to the 5,000 simulations run, the 95th percentile of the default rates' distribution can be estimated robustly.

The sectoral default rates used were determined according to two methods. First, I aggregated the historical sector-level default rates published by *Horváth* (*2021*), and second, I kept the breakdown by main sector. Then, I uniformly increased these initial rates with the macroeconomic PD effect of the scenarios, and then added the PD deflections calculated for 2023. The results are similar for the deflections calculated for the other years, with possible differences only in the amplitude of the effects detected; consequently, no separate calculation was produced for the other years.

Figure 6
Band of loss ratio of banks with and without PD deflections



Note: The relative values represent the ratio of losses for each bank, simulated at the 50th and 95th percentiles with and without the 2023 PD deflection. The figure shows the band of these values for each bank. The left edge of each band indicates the minimum value, the middle line the median, and the right edge the maximum value observed for the banks. The first and second rows show the results for the aggregated historical PD, and the third and fourth the results obtained using a sectoral breakdown of historical PDs.

Figure 6 shows the results of the simulations, both the median of the simulations per bank and the 95th percentile, for both historical default rates determined as above. For aggregated historical PDs, the median – the median of the bank's relative losses – is 99 per cent, indicating a slightly lower loss with deflections than without them. In the case of the most exposed bank, this ratio is 105 per cent. When sector-level default rates are used (Row 3), the relative ratio may be as high as 106 per cent. The largest relative loss ratio difference between banks belonging to the minimum and the maximum is observed for the aggregate default rate and the 95th percentile. Apparently, individual banks are characterised by significant differences, with losses varying by up to 17 per cent for a given risk. These differences between banks may be higher in the case of a scenario that is more severe in terms of transition risks.

The methodology presented here can also be implemented by banks with minor changes. One option, for example, is to implement the effect of the carbon price shock they seek to analyse in their own macroeconomic models through a variable that captures energy prices. Subsequently, using the sectoral methodology outlined, with Equation (6) they can disaggregate the effect for the companies operating in each sector. For some steps, they may also find the partial results of this study helpful.

5. Conclusion

This study presents the methodology and results of a climate stress test carried out for credit institutions, focusing on the methodology of the sectoral module developed for the analysis. The sectoral module diffuses the consequences of the energy price shock caused by carbon pricing between activities with higher GHG intensity and related sectors. The transition shock is diffused across the economy by a sectoral network formed on the basis of the input-output table. The purpose of modelling is to measure the transition risks and not to perform a cost-benefit analysis; accordingly, the positive effects of the transition, occurring mainly in the longer term, are not reflected in the model. Due to the risk focus, the economic stimulus effect of the revenues from carbon pricing were disregarded: despite their ability to significantly mitigate the negative impact on the macro-economy in the short term, their impact on the activities more exposed to transition risks is uncertain.

According to the results of the macroeconomic model, the introduction of carbon prices, modelled as a 100 per cent energy price increase, would, in the short term, cause a 1.2–0.8 per cent GDP decrease compared to the baseline. Based on this, the transition scenario implies a PD increment of 0.2–0.4 percentage points in the short term. According to the results of the sectoral module, the national economy sectors with the highest exposure to transition are those of electricity and gas supply (D), utilities (E), agriculture (A) and mining (B). In addition, the manufacturing (C) and logistics (H) sectors are considered to be vulnerable and have significant bank credit exposures. According to the results of the modelling, the electricity and gas supply sector may suffer the largest PD effect of 1.5–2.3 percentage points compared to the baseline, and the model quantifies a PD effect of 0.3–0.5 percentage points for agriculture, which accounts for 8 per cent of the corporate credit exposure. Given that the transition risks for the sectors are specifically heterogeneous, the transition represents a lower PD increment for many sectors than would otherwise result from a lower GDP path. The credit losses of individual banks also vary depending on the sector to which a particular institution has a higher exposure. According to the simulation used in the research, depending on the calculation method, there may be a 7–17 per cent difference between the banks in terms of the impact of the introduction of transition risks at the sectoral level.

The advantage of the methodology presented lies in its ability, on the one hand, to capture the magnitude of macroeconomic shocks and the fundamental transition differences across sectors, and, on the other, its ease of integration into stress testing processes. As a result of the sectoral module, credit institutions with higher exposures and more vulnerable holdings in sectors exposed to transition risk can also be identified. In addition to the micro-prudential field of use, the methodology can also be used to assess the banks' own risks with minor modifications.

The aim of the short-term exercise is therefore not to carry out a cost-benefit analysis of economic policy responses to climate change, but to examine the stability of the financial system and individual credit institutions in the event of a transition scenario. In the future, the practice can be further developed by incorporating sectoral as well as enterprise-level data when available. Similarly to the sectoral heterogeneity observed in the sectors for transition risks, there may be significant differences between the risks of individual companies within the sectors. For some companies, it is easy to conceive of positive effects from the transition that are currently not adequately handled by the model. Another enhancement option is to refine the network diffusing the primary shocks, for example by using the more detailed corporate-level network of *Borsos – Stancsics* (*2020*).

References

Acemoglu, D. – Aghion, P. – Bursztyn, L. – Hemous, D. (2012a): *The Environment and Directed Technical Change*. American Economic Review, 102(1): 131–166. https://doi.org/10.1257/aer.102.1.131

Acemoglu, D. – Carvalho, V. M. – Ozdaglar, A. – Tahbaz-Salehi, A. (2012b): *The Network Origins of Aggregate Fluctuations*, Econometrica, 80(5): 1977–2016. https://doi.org/10.3982/ECTA9623

ACPR-BdF (2021): *A first assessment of financial risks stemming from climate change: The main results of the 2020 climate pilot exercise*. Analyses et synthèses, No 122. Autorité de Contrôle Prudentiel et de Résolution, Banque de France, Paris. https://acpr.banque-france.fr/sites/default/files/medias/documents/20210602_as_exercice_pilote_english.pdf

Alogoskoufis, S. – Dunz, N. – Emambakhsh, T. – Hennig, T. – Kaijser, M. – Kouratzoglou, C. – Muñoz, M.A. – Parisi, L. – Salleo, C. (2021): *ECB economy-wide climate stress test*. ECB Occasional Paper No 281. https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op281~05a7735b1c.en.pdf

Anufriev, M. – Panchenko, V. (2015)*: Connecting the dots: Econometric methods for uncovering networks with an application to the Australian financial institutions*. Journal of Banking and Finance, 61(S2): 214–255. https://doi.org/10.1016/j.jbankfin.2015.08.034

Baudino, P. – Svoronos, J.-P. (2021): *Stress-testing banks for climate change – a comparison of practices*, Financial Stability Institute Insights on policy implementation, no 34, July. https://www.bis.org/fsi/publ/insights34.pdf

BoE (2019): Bank of England: *The 2021 biennial exploratory scenario on the financial risks from climate change*. Discussion paper, December. https://www.bankofengland.co.uk/paper/2019/biennial-exploratory-scenario-climate-change-discussion-paper

Bokor, L. (2021): *Bank Carbon Risk Index – A simple indicator of climate-related transition risks of lending activity*, MNB Occasional Papers 141. https://www.mnb.hu/letoltes/mnb-op-141-final.pdf

Bokor, L. (2022): *Climate stress test of the Hungarian banking system*, Forthcoming, Magyar Nemzeti Bank.

Boros, E. (2020): *Risks of Climate Change and Credit Institution Stress Tests*. Financial and Economic Review, 19 (4): 107–131. https://doi.org/10.33893/FER.19.4.107131

Borsos, A. – Stancsics, M. (2020): *Unfolding the hidden structure of the Hungarian multi-layer firm network*. MNB Occasional Papers 139. https://www.mnb.hu/letoltes/mnb-op-139-final.pdf

Eurostat (2022a): *Energy imports dependency* (*nrg_ind_id*). https://ec.europa.eu/eurostat/databrowser/view/NRG_IND_ID__custom_2070352/bookmark/table?lang=en&bookmarkId=10efc154-dea6-494c-9867-a3f877a4703c. Downloaded: 24 October 2022.

Eurostat (2022b): *Air emissions intensities by NACE Rev. 2 activity* (*env_ac_aeint_r2*). https://ec.europa.eu/eurostat/databrowser/view/env_ac_ainah_r2/default/table?lang=en. Downloaded: 24 October 2022.

Fazekas, D. – Goldman, M. – Kőműves, Zs. – Pavelka, A. (2021): *Climate impact assessment: Impacts of climate change scenarios on the Hungarian economy*. Cambridge Econometrics, Magyar Nemzeti Bank. https://www.camecon.com/wp-content/uploads/2021/05/MNB_CE_Final_Report_May-2021-2.pdf

Guth, M. – Hesse, J. – Königswieser, Cs. – Krenn, G. – Lipp, C. – Neudorfer, B. – Schneider, M. – Weiss, P. (2021): *OeNB climate risk stress test – modeling a carbon price shock for the Austrian banking sector*. In: Financial Stability Report, Oesterreichische Nationalbank, Issue 42, November: 27–45. https://ideas.repec.org/a/onb/oenbfs/y2021i42b1.html

HCSO (*2005*)*: Az ágazati kapcsolatok mérlegének matematikai feldolgozása* (*Mathematical analysis of the balance of sectoral relations*)*,* 2000. KSH, Budapest. https://www.ksh.hu/docs/hun/xftp/idoszaki/pdf/akmmf2000.pdf. Downloaded: 4 November 2022.

Horvath, M. (2000): *Sectoral shocks and aggregate fluctuations*. Journal of Monetary Economics, 45(1): 69–106. https://doi.org/10.1016/S0304-3932(99)00044-6

Horváth, G. (2021): *Corporate Credit Risk Modelling in the Supervisory Stress Test of the Magyar Nemzeti Bank*. Financial and Economic Review, 20(1): 43–73. https://doi.org/10.33893/FER.20.1.4373

IMF (2022): *Near-Term Macroeconomic Impact of Decarbonization Policies*. In: World Economic Outlook: Countering the Cost-of-Living Crisis, Section 3. https://www.imf.org/-/media/Files/Publications/WEO/2022/October/English/ch3annex.ashx

Königswieser, Cs. – Neudorfer, B. – Schneider, M. (2021): *Supplement to "OeNB climate risk stress test – modeling a carbon price shock for the Austrian banking sector"*. In: Financial Stability Report, Oesterreichische Nationalbank, Issue 42, November: 1–9. https://ideas.repec.org/a/onb/oenbfs/y2021i42b2.html

Nordhaus, W.D. (1993): *Rolling the 'DICE': an optimal transition path for controlling greenhouse gases*. Resource and Energy Economics, 15(1): 27–50. https://doi.org/10.1016/0928-7655(93)90017-O

Ritter, R. (2022): *Banking Sector Exposures to Climate Risks - Overview of Transition Risks in the Hungarian Corporate Loan Portfolio*. Financial and Economic Review, 21(1): 32–55. https://doi.org/10.33893/FER.21.1.32

Soós, G.D. – Kelemen, J. – Horváth, M. (2020): *Polaris, új eszköz a jegybanki előrejelzésekhez* (*Polaris, the new tool for central bank forecasting in Hungary*). MNB Working Papers 1. https://www.mnb.hu/letoltes/mnb-wp-2020-1-final.pdf

Stern, N. (2007): *The Economics of Climate Change: The Stern Review*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9780511817434

Stern, N. – Stiglitz, J.E. – Taylor, C. (2022): *The economics of immense risk, urgent action and radical change: towards new approaches to the economics of climate change*. Journal of Economic Methodology, 29(3): 181–216. https://doi.org/10.1080/1350178X.2022.2040740

TCFD (2017): *The Use of Scenario Analysis in Disclosure of Climate-Related Risks and Opportunities*. Technical Supplement. https://assets.bbhub.io/company/sites/60/2021/03/FINAL-TCFD-Technical-Supplement-062917.pdf. Downloaded: 21 July 2022.

Vermeulen, R. – Schets, E. – Lohuis, M. – Kölbl, B. – Jansen, D.-J. – Heeringa, W. (2018): *An energy transition risk stress test for the financial system of the Netherlands*. DNB Occasional Studies 16-07, De Nederlandsche Bank. https://www.dnb.nl/media/pdnpdalc/201810_nr-_7_-2018-_an_energy_transition_risk_stress_test_for_the_financial_system_of_the_netherlands.pdf