LÁSZLÓ BOKOR

CLIMATE STRESS TEST OF THE HUNGARIAN BANKING SYSTEM

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Climate stress test of the Hungarian banking system

(A magyar bankrendszer klímastressztesztje)

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Contents

Abstract

This paper presents the pilot top-down climate stress test of the Hungarian banking system over the 2020-2050 horizon. The focus is on a core indicator of financial soundness, the ratio of non-performing loans. Three scenarios are considered with different grades of compliance with the Paris Agreement. Results show that, by 2050, the sectoral excess ratios of non-compliance are scattering from 0 to 19 percentage points.

Keywords: climate stress test, banking system, non-performing loans, sectoral granularity
JEL codes: C51, C53, G21, Q54

Összefoglaló

Ez a tanulmány a magyar bankrendszer 2020-2050 közötti időszakra vonatkozó pilot top-down klímastressztesztjét mutatja be. Középpontban a pénzügyi stabilitás egyik fő mutatója, a nemteljesítő hitelek aránya áll. Három, a Párizsi Megállapodásnak való megfelelés különböző fokozatait megtestesítő forgatókönyv lett megvizsgálva. Az eredmények azt mutatják, hogy 2050-re az egyes ágazatok nemteljesítési arányainak többlete 0 és 19 százalékpont között szóródik.

1 Introduction

The gathering storm clouds of climate change challenge our current way of being, not only in the economy but in our everyday lives as well. The exposure of different actors, however, varies considerably over space and time. For example, the rising global frequency and magnitude of droughts, floods, wildfires, and the collapse of biodiversity affects a European agricultural firm quite differently than one located close to the Equator, or a microelectronic company anywhere in the world. Also, an ambitious path for a carbon tax affects a coal-fired power plant and a software development company completely differently.

Physical and transition risks (i.e. impacts of gradual warm-up and extreme weather events on physical capital and economic performance, and impacts of related decarbonisation policies) influence default risks, which have an impact on bank solvency depending on the structure of loan exposures. Thus, it is no surprise that more and more central banks (and other institutions responsible for financial stability) have decided to bring these steadily intensifying challenges to the forefront of public debate. Globally, we are still at the very beginning of the progress, only at the stage of knowledge accumulation. Consequently, at this point, the goal should not be supervision and sanctioning, but rather a warning and a call for the dialogue between stakeholders. The Magyar Nemzeti Bank (MNB), which is also part of this pioneering process, prepared its first pilot 30-year pilot climate stress with a focus on the quality of bank loans (the project was based on information up to 2020 Q4).

Several prerequisites must be met to test the climate soundness of the financial system. First, the factors influencing global warming (e.g. concentration of greenhouse gases in the atmosphere) need to be translated into economic realities. Second, for the reasons discussed above, this must be carried out in a sectoral disaggregation. Third, two-way feedback mechanisms between natural and economic modules should be incorporated. This feature is essential for the coherent derivation of the different physical and transition consequences of various policies. In this experimental project, the climate-informed economic model of Cambridge Econometrics (CE) was utilised to obtain the sectoral economic data. Based on a selected group of economic variables it provided, I have mapped the ratio of non-performing loans to economic realities and made conditional forecasts for 2020-2050 in a sectoral disaggregation covering all (non-financial) activities. As a result, excess ratios of non- and imperfect compliance paths are presented, along with the HUF amount of these excess risks assuming static distribution of loan portfolio.

2 Climate-informed economic variables

CE's demand-driven macro-sectoral econometric model, called E3ME, has been continuously developed for 30 years. It integrates global economic, energetic, and environmental processes, i.e. it is an integrated assessment model (IAM) which is suitable for running climatic scenarios.[1] In line with post-keynesian economics, it has the following properties (see Pollitt 2018):

- Agents lack perfect knowledge, and thus
  - there is no guarantee that the economy works on full capacity;
  - regulatory measures could improve environmental and economic outcomes.
- There is strong path dependency in the underlying equations.
- Parameter calibration is based on time series (i.e. "macroeconometric"), and thus agents behave as they did in the past (recall Lucas critique).
- Technology is treated endogenously by sector diffusion algorithms.
- Money supply is endogenous.
- Wages does not automatically adjust to market clearing levels.
- Air pollution has health and thus economic impact.

Based on predefined policy and regulatory assumptions and the consequent development of factors affecting the climate, it provides the projected paths of several sector-level economic variables (investment, exports etc.). Note, however, that physical risks are only calculated on the level of gross value added and not that of its components. Since E3ME allows the economy to operate below potential output (i.e. there can be, and usually are, free capacities), and assumes that supply adapts to demand (subject to any constraints), it usually reaches very different conclusions compared to general equilibrium models when examining the impacts of various policies.[2]

CE prepared three scenarios for the MNB with a horizon of 2050: orderly transition (OT), failed transition (FT), disorderly transition (DT). The first two are in line with the related NGFS (2020) narratives, but the latter is not. In orderly transition, countries that have ratified the Paris Agreement take further decarbonisation steps in addition to their previous commitments.[3] As a result of these actions, global temperatures are expected to be less than 1.5 degrees Celsius above the "pre-industrial" level of the second half of the 19th century by the end of 2100.[4] It is assumed that most sectors fall under the umbrella of a global emission trading scheme with rising carbon prices, renewables receive high subsidies and feed-in tariffs, mandates on the ratio of electric vehicles and biofuel blending are tightened, energy-efficiency investments are at a high level, and significant investments are made in carbon capture and storage technologies. The basis for Hungary-specific assumptions (in addition to EU-specific ones, which are qualitatively similar to the global ones in this scenario) is the National Energy and Climate Plan (NECP) of 2020-2030 (see ITM 2019). Hungarian subsidies and investments are solar-focused, that is, wind energy, for example, suffers a severe disadvantage.

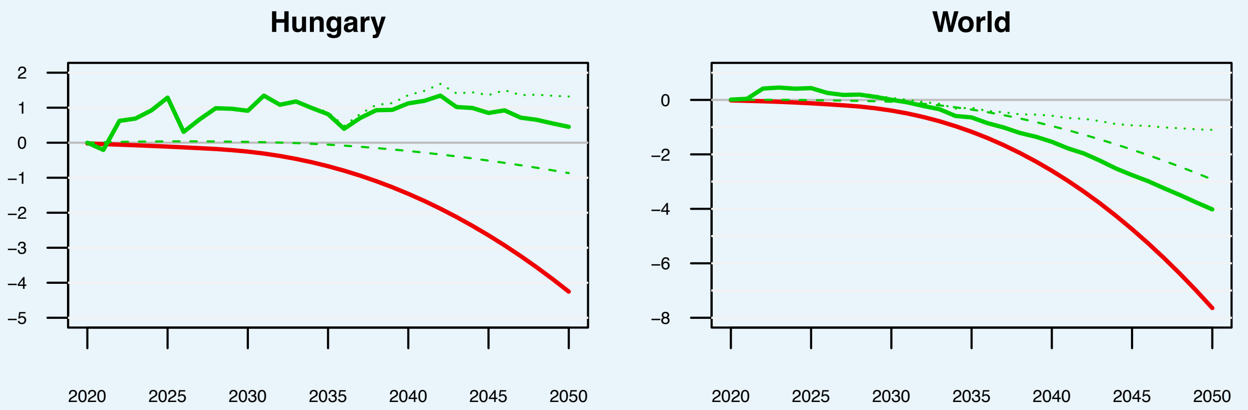
[1] For a multitude of relevant modelling approaches, see NGFS (2020), p. 23.
[2] For a complete technical presentation of E3ME, see CE (2019).
[3] For nationally determined contributions, see UNFCCC (2021).
[4] 1850-1900 is the best documented period of low carbon emission era. There are, however, other periods to consider. Hawkins et al (2017) argues for the 1720-1800 period as benchmark.

The counterpart is the failed transition scenario. In this scenario, the previously announced climate and energy policy measures remain in force, but beyond these no new aspirations are articulated (as a result of which excess global temperature will rise to about 3.6 degrees Celsius). In this case, the world does the business as usual, the EU ETS continues to operate with the current low carbon prices, the specifications on biofuel blending and the subsides of renewables and energy-efficiency projects remain modest. Specific Hungarian assumptions continue to be based on NECP 2020-2030 with slower removal of carbon usage and more moderate solar investments.

The disorderly transition scenario embodies an intermediate trajectory in which implementation of the principles set out in the Paris Agreement is the same as in orderly transition, but the financial system starts to price in climate risks belatedly in a swift manner (after 2025). In this scenario, the excess physical damages compared to orderly transition are avoided, but since the measures are implemented unexpectedly, they come with negative (basically temporary) economic shocks.

For the interpretation of various future macroeconomic paths and their underlying risks, the introduction of the concept of "climate-uninformed baseline" (CUB) is necessary. It indicates the hypothetical trajectory that would occur in the absence of additional decarbonisation steps, but without its destructive physical consequences. That is, it is the failed transition scenario free of physical risks. Figure 1 shows the projected effects for Hungarian and world GDP in the two extreme cases. Note that all CE data are modelled from 2019.

Figure 1
GDP effects of physical and transition risks
[difference from CUB GDP levels in percent]



Legend: Red - FT (physical only), Green - OT (physical - long dashed, transition - short dashed)
Own figures. Data: CE.

In case of failed transition, Hungarian GDP level are expected to be 4.25 percent lower than that of CUB by the end of 2050 due to the physical consequences of climate change. However, the road up to this point is at least as important: we are not dealing with a one-off negative shock in the distant future, but a path in which, year after year, there will be (relatively) fewer and fewer goods to share.

On the contrary, in the case of orderly transition, the physical effects are significantly reduced in parallel with the more subdued rise in global temperature. Moreover, CE's E3ME model suggests that the transition is actually not a risk, but rather an opportunity for the Hungarian economy since it entails GDP surplus. It also implies that physical and transition risks in Hungary are not antagonists in most of the sectors. The combined effect of the risks is also positive, which conveys the message that an orderly global (including Hungarian) transition to a climate-friendly operation is highly desirable for the Hungarian economy. At global level, however, it is not the perception at all. Figure 1 makes it clear that even though the transition is desirable, it is far from being a triumphal march. That is, several countries are expected to pay heavy price, regardless of the action or inaction of international community.

Figure 2 breaks down the Hungarian transition risks of Figure 1 into its main elements.

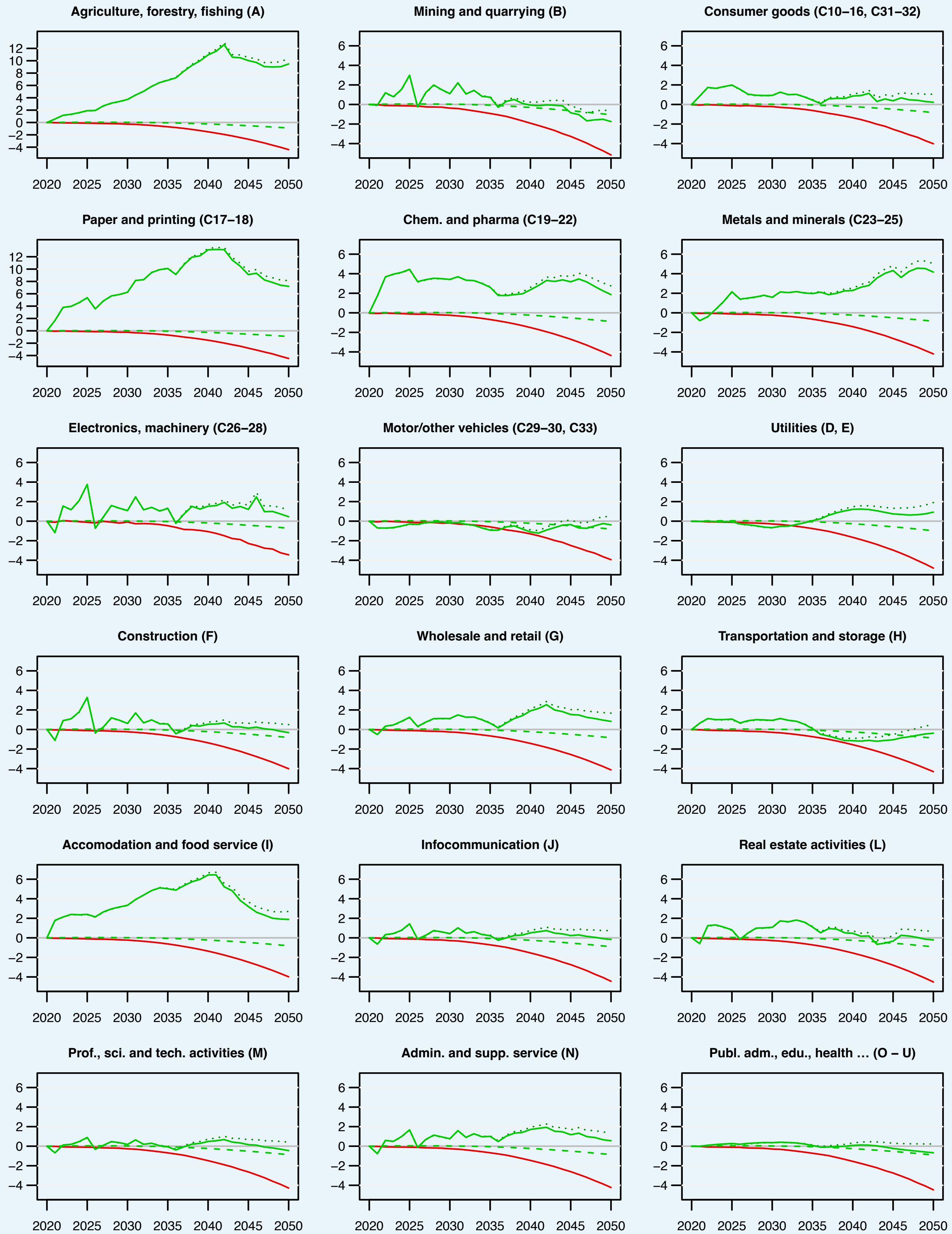
Figure 2
Decomposition of the GDP effects of transition risks
[difference from CUB GDP levels in percent]

Own calculations. Underlying data: CE.

On the aggregate level, the main drivers of the economic transition are investment and net export. It implies the rising investment in key infrastructures that are to be decarbonised, i.e. energy production and transportation (e.g. railways). Construction, metal, and electronics industry also benefit from these investments. The restructuring of the automotive industry to more fuel-efficient or electric-powered technologies also provides a (temporary) impetus for investment and foreign trade in the related sectors.[5] The conditions for sectors producing and using fossil fuels deteriorate. Nevertheless, the balance of trade is greatly improved by declining fuel imports, which allows a larger portion of household income to be spent on other products. This new-found income boosts the output of the agriculture, food production and consumer goods sectors. Consumption is also strengthened by the model assumption that the government cuts VAT revenue by the amount of revenue it raises from a carbon tax. In the later stages, however, when energy efficiency becomes prevalent, consumption becomes more restrained. For an exhaustive description of assumptions and causalities, see CE (2021).

[5] Note that in a global economic model the increasing income of foreign trading partners expands their imports.

Figure 3
Sectoral GVA effects of physical and transition risks
[difference from sectoral CUB GVA levels in percent]



Legend: Red - FT (physical only), Green - OT (physical - long dashed, transition - short dashed)
Own figures. Data: CE.

Figure 3 shows the projected effects of physical and transition risks on sectoral gross value added (GVA) in the two extreme scenarios.[6] In failed transition, physical risks entail continuously evolving costs, up to 3.4 to 5.2 percent of the sectoral GVAs by 2050. By contrast, in the orderly transition, physical risks are reasonably lower by the end of the examined period: they amount to 0.7 to 1.1 percent, while economic transformation gives an extra boost for most of the sectors. This dominant group not only avoid the harsh negative consequences of inaction but take advantage of newly opened-up opportunities. That is, they can exceed the hypothetical paths of the climate-uninformed world. There are some exceptions, e.g. manufacture of vehicles. Of course, thanks to the transition, they can remain close to their CUBs and so avoid the much worse paths of failed transition.

It should be noted, however, that sectoral paths imply more or less dispersed paths at the firm level. For example, at least for now, the available green solutions for car manufacturers are more advanced than for truck manufacturers. On the other hand, trucks are less expandable in the economy. Both parties have to deal with stranded assets though (similar to carbon-intensive units, such as coal-fired power plants).

[6] Recall that the difference between disorderly and orderly transition is mostly temporary and concentrated around 2025.

3 Focusing on NPL ratio

Conventional 2-3-year financial stress tests are comprehensive, and thus they imply the projections of a multitude of elements of balance sheet and income statement for solvency calculations. The question is how realistic is to model the full spectrum of credit, market, operational, liquidity etc. risks over a 30-year period in a top-down manner. This would require a myriad of assumptions (e.g. about the future behavioural function of individual banks), which would make the interpretability of findings highly questionable. According to the principle of subsidiarity, such an exercise seems more sensible using a bottom-up approach, i.e. in which the banks themselves perform the analyses based on climate scenarios defined and provided by the relevant authority. It is certainly no coincidence that even well-resourced institutions such as the French central bank in cooperation with the prudential supervision authority (Allen et. al 2020) or the British central bank (Bank of England 2019) follow the bottom-up approach. Nevertheless, a recent paper of European Central Bank (Alogoskoufis et al. 2021) shows an ambitious top-down exercise by incorporating credit and market risks, and, for the time being, assuming static balance sheet.

In this paper, I focused on the ratio of non-performing loans to total loans.[7] I chose this indicator, which is one of the core measures of financial soundness (see e.g. IMF 2019), because of its relative autonomy. I argue that it is *relatively* less dependent on influencing factors other than pure economic variables, compared to contenders such as earnings or capital.

Empirical evidence underscores that ability-to-pay depends positively on economic growth. Theoretically, by easing or tightening credit ratings, banks could indirectly shift the probability of default and thus could weaken the validity of previously observed connections between economic conditions and payment ability. In practice, however, the compliance with capital requirements and the goal of profit maximization leave less room for this kind of discretionary behaviour. While other core indicators are affected by cycles as well, they are significantly influenced by additional motifs. For example, pre-tax earnings are affected by bank decisions about provisions (e.g. for expected credit losses) or write-offs. Retained earnings are affected by dividend decisions. Capital adequacy is affected by the capital injection decisions of foreign parent bank (which may also operate in a very different macroeconomic environment). Accordingly, it seems less plausible to map these variables to pure economic variables.

In the analysis, I took the following assets into account: end-of-month transaction-level (on-balance and off-balance sheet) outstanding principals of HUF and FX credits, loans, credit-type agreements, financial leases (hereafter together "loans") provided by other monetary financial institutions to non-financial companies.[8] This data is available in NACE (rev2) level 2 granularity, but only from April 2012. Moreover, the repayment moratorium, which came into force on 18 March 2020 in Hungary, also represents a major challenge as it cut the link between economic situation and payment ability, i.e. it practically shortened the sample available.

The issue of flows from banks to factoring companies also had to be examined. If factoring were prevalent, we could get a biased picture of the relationship between economic situation and non-performance if only the non-performing loans held in banks' portfolios were considered. My analysis showed that, at the system level, this activity affects only a minor percent of non-performing loans, and thus I ignored these flows.[9]

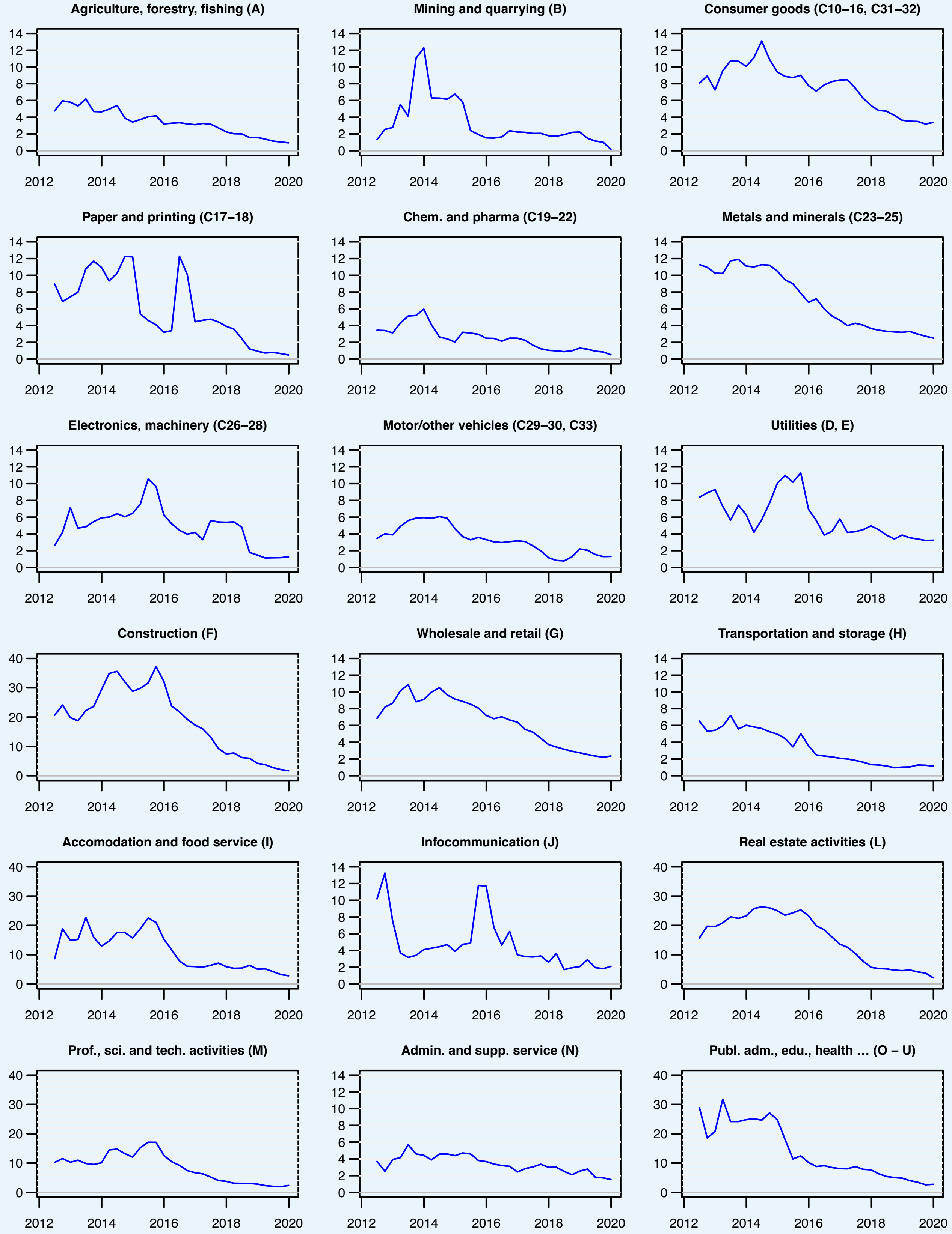
Figure 4 shows the available samples. Although the levels of ratios are markedly different, the downward movement is perceptible in parallel with the economic upturn from 2013-14. The available sample is too small to encompass a full cycle, but it does include a small bust period in 2012-2013. Thus, the models can be trained on varied data.

[7] A loan is non-performing if repayments are 90+ days past due.

[8] Sectoral classification of foreign companies not having a Hungarian tax number, sole traders and proprietorships are in whole or in part incomplete, and so I also excluded them from the calculations. All of these excluded items account for only one fifth of the total outstanding principals on average during the examined period.

[9] Nevertheless, at the bank level, the tolerated ratios of non-performing loans are diverse.

Figure 4
Historical NPL ratios
[2012 Q2 - 2019 Q4, in percent]



Own figures. Data: MNB.

4 Framework for translating economic data to NPL ratios

CE provided the time series of six original variables of dominantly NACE level 1 activities: investment, export, import, number of employees, unit labour cost (ULC), gross value added (GVA). One crucial problem was, however, that E3ME is not capable of providing physical risks for all of these variables but only for GVA. A comprehensive climate assessment, however, requires not only the incorporation of transition risks but also physical risks. Moreover, in light of the relatively short loan series, another critical issue was the annual frequency of CE data.

Under these circumstances, my approach was the following: (i) exploiting all available information using as many explanatory variables as possible, (ii) keeping degrees of freedom at the maximum, (iii) with the goal of making conditional point forecasts. To solve this puzzle, we should start at the end, i.e. at the ultimate goal. Recall that only GVA data contains both physical and transition risks. It follows that it plays the title role when projecting various NPL-ratio scenarios. But it also implies that set(s) of predictor variables that are strongly related to GVA should not be incorporated into the model.[10] Both macroeconomic theory and actual data suggest two such variables: import and number of employees. The remaining set of variables are relatively less correlated with GVA. Investment telegraphs interest rate conditions, export represents foreign demand, and ULC is an important indicator of business conditions, including the potential deficiencies of labour taxation policies.

It is generally true that even less accurate high frequency data are preferable to more accurate low frequency data. No wonder that interpolation methods are widely used in official statistics. I converted annual sectoral CE data to quarterly using the Cholette (1984) modification of Denton's (1971) method. For a crosscheck, I also converted the series of aggregated GVAs and found that it was nicely in line with Eurostat's quarterly GDP data.[11] This is not a surprise at all, for two reasons: First, the aggregate annual GVA of CE was derived from Eurostat GDP. Second, although Eurostat recently uses the method of Chow and Lin (1971) by national accounts, it used to apply that of Denton (see Eurostat 2016).

Not only logic, but also empirics suggest the strong connection between economic performance and payment ability. Beck et al. (2013) showed the negative impact of GDP growth to NPL ratio on a 75-country dataset. Based on long Eurozone time series, Sørensen et al. (2009) showed the cointegrating relationship between loan demand of non-financial companies and economic variables including GDP, and that loans depended positively on GDP. These suggest, however, that the ratio of non-performing loans (ceteris paribus) is expected to be "normal" in a stable economic situation, i.e. when output is close to the potential, below normal when there is a boom, and above normal when there is a bust. On these grounds, NPL ratios are expected to be level stationary.

Modelling possible cointegrating relationships in our case would have been futile. Small sample with interpolated sectoral variables might have not in themselves advocate this, but the real obstacle was the unfulfilled prerequisite for making coherent conditional forecasts on this basis (recall, all variables but GVA lack the physical risks). Thus, I decided on an unusual procedure: I took the "gap" of all economic variables as is conventional the case with output. When calculating gaps, I always used the full samples available, and so lots of information outside training period could be also incorporated. Table 1 summarises the original variables, their transformations and their usage in model estimation and forecasting.

[10] High collinearity is not a pairwise property, but that of sets of explanatory variables.
[11] In this crosscheck, naturally, GVA of financial and insurance activities (K) was also involved.

Table 1
Variables

Original variables (levels)	Unit	Time, Frequency	My variables (ratios)	Transformation steps on full sample	Usage e.: 2012 Q2 -2019 Q4 f.: 2020 Q1 -2050 Q4
GVA (CUB)	million EUR (2018)	1995-2050 annual	GVAgap	1. Denton-Cholette year-to-quarter frequency conversion 2. Univariate HP filter (λ=1600) → cycle, trend[12] 3. gap := cycle / trend	estimate
Investment (CUB)			Igap		estimate, forecast
Export (CUB)			Xgap		
ULC (CUB)	thousand EUR (2018)	2010-2050 annual	ULCgap		
GVA (OT)	million EUR (2018)	1995-2050 annual	GVAgap (OT)	1. Denton-Cholette year-to-quarter frequency conversion 2. cycle := GVA (scen) - GVA (CUB) trend 3. gap := cycle / GVA (CUB) trend	forecast
GVA (FT)			GVAgap (FT)		
GVA (DT)			GVAgap (DT)		
Non-performing loans	HUF (current prices)	2012 M4-2019 M12 monthly	NPL	1. Month to quarter by averaging 2. Non-performing loans / total loans	estimate

Own table. Sources of series: CE (VA and ULC levels), MNB (loan levels).

A sluggish stationary process can be easily interpreted as nonstationary by looking at the data alone. As a practical example, test results of several realizations of a simple AR(1) process with a coefficient closer to one can show "instability" even for a sample of few hundred data points. Nevertheless, the KPSS test (Kwiatkowski et al. 1992) with Bartlett kernel and Newey-West bandwidth fails to reject the null hypothesis of level stationarity of NPL ratios at significance level of 1 percent (in some cases at 5 percent). With quadratic spectral kernel, which suggests a more accurate estimate of long-run variance in medium-size samples (see Hobijn et al. 2014), the p-values are even more elevated. In the case of explanatory variables, the null cannot be rejected at a significance level of 1 percent (at 5 or 10 percent, it is nine-tenth or two-thirds of the cases), which suggests level stationarity even more. Moreover, as Jönsson (2011) showed, the small-sample critical values of KPSS can be much higher than asymptotic critical values, i.e. the test has a considerable upward size distortion in finite samples. Consequently, I consider the transformed variables level stationary.[13]

The uniform model estimated on sample 2012 Q2 - 2019 Q4 was

$$NPL_t = \beta_0 + \beta_1 Igap_t + \beta_2 Xgap_t + \beta_3 ULCgap_t + \beta_4 GVAgap_t + \varepsilon_t \,,$$

where $\varepsilon_t \sim N(0, \sigma^2)$. The method was OLS.

For most sectors, Jarque-Bera (1987) tests did not reject the null of normality of residuals. Similar is the picture when testing for heteroskedasticity using Koenker's (1981) studentized version of Breusch-Pagan (1979) test. At the same time, (typically first-order) autocorrelation showed up in most cases with Breusch-Godfrey test (Breusch 1978, Godfrey 1978). Since lagged response variable was not included as explanatory variable, the OLS parameter estimates remained unbiased but not the standard errors. Thus, I used Newey and West's (1987) heteroskedasticity and autocorrelation-consistent (HAC) estimator to obtain the "true" standard deviations of coefficients. The quotation marks might be justified because of the known size distortion of HAC.[14] Although it distorts typically upwards, it is reassuring to a certain extent that the p-values of t-test of GVA gaps are generally extremely small.

[12] Hamilton (2018) strongly opposes the use of Hodrick and Prescott's (1997) filter for multiple reasons and proposes an alternative detrending method. Note, however, that it is based on "lagging", which is not a desirable solution in our case. Moreover, Dritsaki and Dritsaki (2022) argue that the Hamilton filter might have flaws.

[13] It is less known that a relationship between sluggish stationary variables might also be spurious (see Granger et al. 2001). Nevertheless, in the case of loan performance and economic performance, empirics proved that they are not independent.

[14] The nonparametric bandwidth selection of Newey and West (1994) which I have applied does not amend this problem.

Table 2
Model estimates (NPL ratio as regressand)

Agriculture, forestry, fishing (A)

	Coef.	Pr(>|t|)	VIF
c	0.0326	0.0000	NA
Igap	−0.0287	0.2325	1.3527
Xgap	−0.3739	0.0008	1.8466
ULCgap	−0.0954	0.0301	3.2144
GVAgap	−0.1006	0.0265	5.0803
	Adj. R2	**JB**	
	0.7064	0.2802	

Mining and quarrying (B)

	Coef.	Pr(>|t|)	VIF
c	0.0327	0.0000	NA
Igap	−0.0089	0.2227	1.9069
Xgap	−0.6056	0.0000	1.0310
ULCgap	−0.4676	0.0042	4.2930
GVAgap	−0.0887	0.2761	4.2452
	Adj. R2	**JB**	
	0.5674	0.0026	

Consumer goods (C10–16, C31–32)

	Coef.	Pr(>|t|)	VIF
c	0.0806	0.0000	NA
Igap	−0.0408	0.0867	1.6082
Xgap	−0.0748	0.4724	1.7798
ULCgap	−0.1881	0.2602	1.7289
GVAgap	−0.6740	0.0000	1.6740
	Adj. R2	**JB**	
	0.8350	0.5505	

Paper and printing (C17–18)

	Coef.	Pr(>|t|)	VIF
c	0.0579	0.0000	NA
Igap	0.0856	0.0000	3.7804
Xgap	−0.6760	0.0000	3.6083
ULCgap	−0.0671	0.1564	2.5196
GVAgap	−1.3619	0.0000	1.2459
	Adj. R2	**JB**	
	0.7807	0.0914	

Chem. and pharma (C19–22)

	Coef.	Pr(>|t|)	VIF
c	0.0245	0.0000	NA
Igap	−0.0677	0.0000	2.6684
Xgap	0.1960	0.0286	3.4367
ULCgap	−0.1314	0.0034	3.3056
GVAgap	−0.1815	0.0000	1.6651
	Adj. R2	**JB**	
	0.8545	0.7921	

Metals and minerals (C23–25)

	Coef.	Pr(>|t|)	VIF
c	0.0677	0.0000	NA
Igap	−0.3295	0.0000	1.6783
Xgap	−0.1981	0.0000	1.5859
ULCgap	−0.4263	0.0000	2.1022
GVAgap	−0.5469	0.0002	1.9499
	Adj. R2	**JB**	
	0.9146	0.0692	

Electronics, machinery (C26–28)

	Coef.	Pr(>|t|)	VIF
c	0.0484	0.0000	NA
Igap	−0.2084	0.0000	1.3921
Xgap	−0.3206	0.3642	2.0687
ULCgap	0.0912	0.3894	1.4927
GVAgap	0.1512	0.1845	1.7563
	Adj. R2	**JB**	
	0.5909	0.5099	

Motor/other vehicles (C29–30, C33)

	Coef.	Pr(>|t|)	VIF
c	0.0349	0.0000	NA
Igap	−0.0570	0.0003	1.6560
Xgap	−0.0235	0.7863	1.6759
ULCgap	−0.2094	0.0000	1.0230
GVAgap	−0.3696	0.0000	1.4005
	Adj. R2	**JB**	
	0.6514	0.7106	

Utilities (D, E)

	Coef.	Pr(>|t|)	VIF
c	0.0680	0.0000	NA
Igap	0.0325	0.1787	1.6004
Xgap	0.3184	0.0014	5.4657
ULCgap	0.1753	0.3438	1.7571
GVAgap	−0.7363	0.0011	6.0294
	Adj. R2	**JB**	
	0.7017	0.7749	

Construction (F)

	Coef.	Pr(>|t|)	VIF
c	0.1516	0.0002	NA
Igap	−0.3106	0.4074	3.8252
Xgap	9.6542	0.0039	1.9158
GVAgap	−0.2821	0.4491	5.0599
	Adj. R2	**JB**	
	0.3482	0.4709	

Wholesale and retail (G)

	Coef.	Pr(>|t|)	VIF
c	0.0691	0.0000	NA
Igap	−0.2378	0.0000	2.2002
Xgap	−0.1049	0.0191	1.3956
ULCgap	−0.5359	0.0000	1.2315
GVAgap	−0.1584	0.2563	2.2326
	Adj. R2	**JB**	
	0.7669	0.3578	

Transportation and storage (H)

	Coef.	Pr(>|t|)	VIF
c	0.0355	0.0000	NA
Xgap	−0.0941	0.0000	1.1572
ULCgap	−0.2560	0.0000	1.2456
GVAgap	−0.6946	0.0000	1.1015
	Adj. R2	**JB**	
	0.9217	0.6263	

Accomodation and food service (I)

	Coef.	Pr(>|t|)	VIF
c	0.1255	0.0000	NA
Igap	0.1734	0.0643	1.6019
ULCgap	−1.9604	0.0000	1.9501
GVAgap	−3.2418	0.0000	2.6889
	Adj. R2	**JB**	
	0.7214	0.8188	

Infocommunication (J)

	Coef.	Pr(>|t|)	VIF
c	0.0510	0.0000	NA
Igap	−0.0289	0.8742	5.5393
Xgap	−0.9072	0.2484	1.6272
ULCgap	−0.0826	0.7983	1.4913
GVAgap	−1.0504	0.2277	6.1758
	Adj. R2	**JB**	
	0.3585	0.0101	

Real estate activities (L)

	Coef.	Pr(>|t|)	VIF
c	0.1483	0.0000	NA
Igap	0.4196	0.0003	1.2723
ULCgap	−1.8644	0.0000	1.7082
GVAgap	−3.3569	0.0000	1.8217
	Adj. R2	**JB**	
	0.8800	0.0000	

Prof., sci. and tech. activities (M)

	Coef.	Pr(>|t|)	VIF
c	0.0853	0.0000	NA
Igap	−0.1717	0.0030	1.7373
Xgap	−0.0143	0.6013	1.1971
ULCgap	−1.0043	0.0000	1.4942
GVAgap	−1.8851	0.0000	1.1263
	Adj. R2	**JB**	
	0.9195	0.7537	

Admin. and supp. service (N)

	Coef.	Pr(>|t|)	VIF
c	0.0354	0.0000	NA
Igap	−0.0053	0.6256	2.8350
Xgap	−0.0371	0.0259	1.1649
ULCgap	0.1240	0.0345	2.8447
GVAgap	−0.5346	0.0000	1.4516
	Adj. R2	**JB**	
	0.6743	0.5802	

Publ. adm., edu., health … (O – U)

	Coef.	Pr(>|t|)	VIF
c	0.1113	0.0000	NA
Igap	0.1011	0.0018	1.4280
Xgap	−1.1352	0.0060	2.7052
ULCgap	−1.6857	0.0000	3.4712
GVAgap	−2.5867	0.0000	1.8429
	Adj. R2	**JB**	
	0.8247	0.0000	

Sample: 2012 Q2 - 2019 Q4. Variables are in ratio. Method is OLS. The t-tests are based on HAC (Newey-West) standard errors. There is no foreign trade in I and L. ULCgap / Igap was omitted for sector F / H due to high multicollinearity (VIF>10) affecting GVAgap. Figure A1 (in appendix) shows the relationship between NPL ratio and GDPgap.

Table 2 summarises the estimates and related tests. Most models reliably capture the inverse relationship between the cyclical situation and non-payment. That is, economic boom go hand in hand with lower NPL ratio and vice versa. The sensitivity to cycles is quite diverse though. In five models (B, C26-28, F, G, J), the GVA gap proved to be statistically insignificant (and thus there is no significant difference between forecasted scenarios of NPL ratio, see later). Note that, in two cases (F, H), strong multicollinearity showed up by GVA gap, which would have made its parameter estimates less reliable, and so the variables concerned were omitted.

Note that it is not the scope of this study to build unique models for unconditional forecasts but to make forecasts *conditional upon* the estimated relationships over the full sample and the given future paths of explanatory variables. Nevertheless, the parameters seem to be robust to sampling. After chopping four quarters from the end of the sample, estimates showed very similar outcomes, which does not suggest overfitting.

The forecast period of the NPL ratio is 2020 Q1 - 2050 Q4. The idea is that ex-ante static projections are made by feeding the estimated models with the given CUB gaps, while physical and transition risks are encapsulated entirely into the GVA gap. Formally,

$$NPL_T^{scen} = \hat{\beta}_0 + \hat{\beta}_1 Igap_T^{CUB} + \hat{\beta}_2 Xgap_T^{CUB} + \hat{\beta}_3 ULCgap_T^{CUB} + \hat{\beta}_4 GVAgap_T^{scen} \ .$$

It follows that the differences in forecasted NPL-ratio paths of scenarios are up to the differences in GVA gaps which are assumed to be the gap between the level of the actual scenario and the trend of CUB level (see Table 1). In 2 cases out of 18 sectors (C17-C18 and I), the forecasted NPL ratios would go below zero, and so they were left-censored.

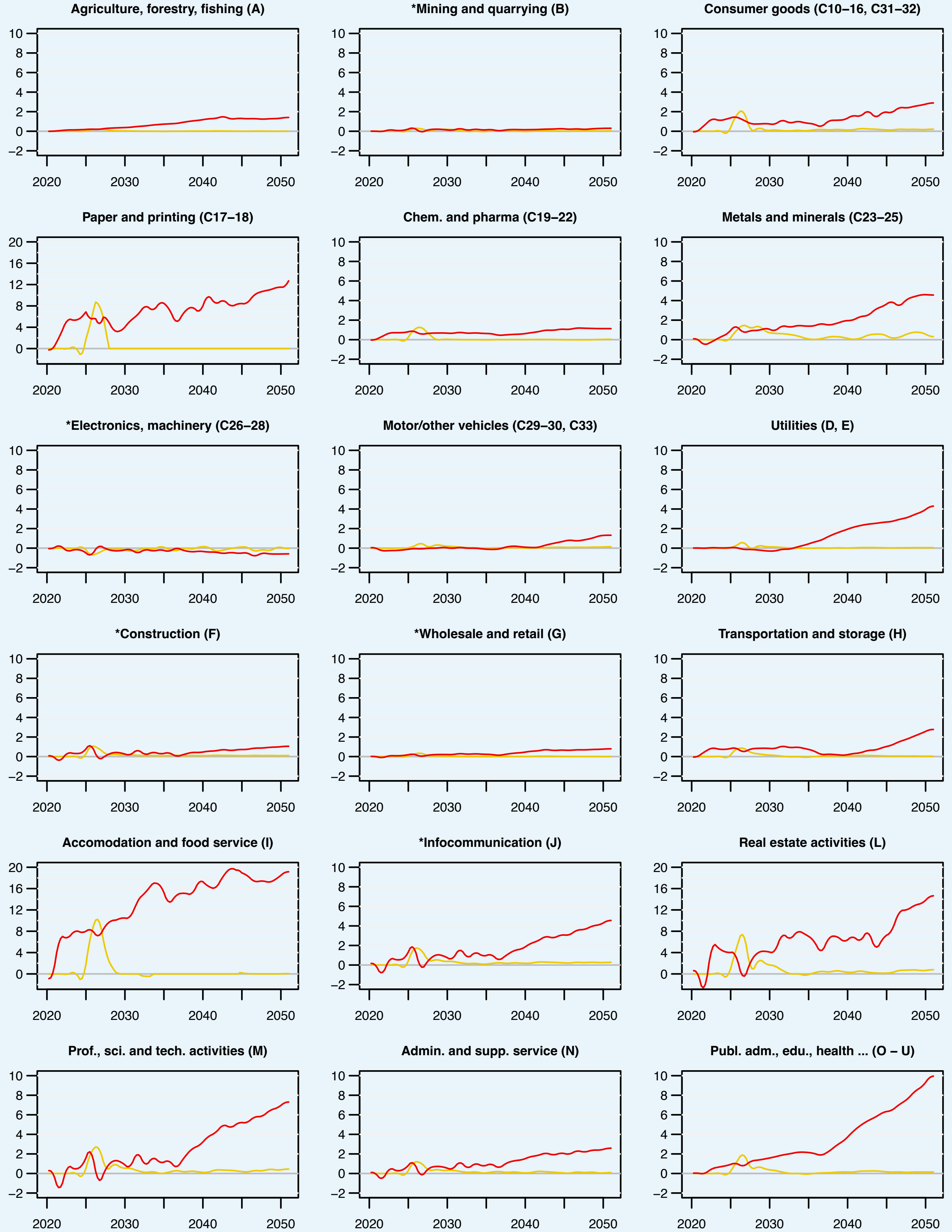
5 Excess NPL in adverse scenarios

Figure 5 shows the differences between point forecasts of failed/disorderly transition and orderly transition. The main message is that the debt payment ability of various industries and hence the risks run by banks can show huge differences depending on the global (including Hungarian) economic paths examined. In failed transition, for example, real estate activities (L) could see an excess of about 14 percentage points in NPL ratios by 2050, primarily because of its high cyclical sensitivity. Accommodation and food services (I) shows similar cyclical sensitivity and physical risks of failed transition, but it expects a net benefit from transition that real estate activities (L) do not (see Figure 3 and Table 2). Thus, sector I's excess is a few percentage points higher than L's by 2050. By contrast, even though the figures of paper and printing (C17-18) convey similar excess, the composition of underlying factors are quite different. Its huge net benefit of orderly transition is balanced by low cyclical sensitivity. Overall, sectoral models suggest a permanent deterioration in loan quality (in relative terms) as a consequence of doing business as usual rather embarking on the path of orderly transition. In disorderly transition, the effects are mostly temporary and concentrated after 2025, but there are a few exceptions (metals, construction, real estate).

Naturally, it must be kept in mind that a certain level of excess NPL ratio means completely different things in an industry with high solvency than in one with low solvency. For example, in a historical context, the NPL ratio of construction (F) is higher than that of chemicals and pharmaceutical (C19-22) by an order of magnitude (see Figure 4). One percentage point excess in NPL ratio might be imperceptible for one, and very unusual for the other.

Concerning the banking system (or individual banks), the extent of excess risk depends on the abovementioned factors and the distribution of loan exposures. Figure 6 demonstrates the excess risks on the basis of static amounts of 2019 Q4 loans, i.e. it shows the product of excess NPL ratios and 2019 Q4 loans. Huge loans and strongly diverging paths of NPL ratios stand behind the values of real estate activities (L), making it an outlier. Professional, scientific and technical activities (M) are among the largest borrowers and its NPL ratio excess jumps by 2050; consequently its high position is also not surprising. On the other hand, accommodation and food service (I) has far less loans, while its excess NPL ratio was seen to be the largest.

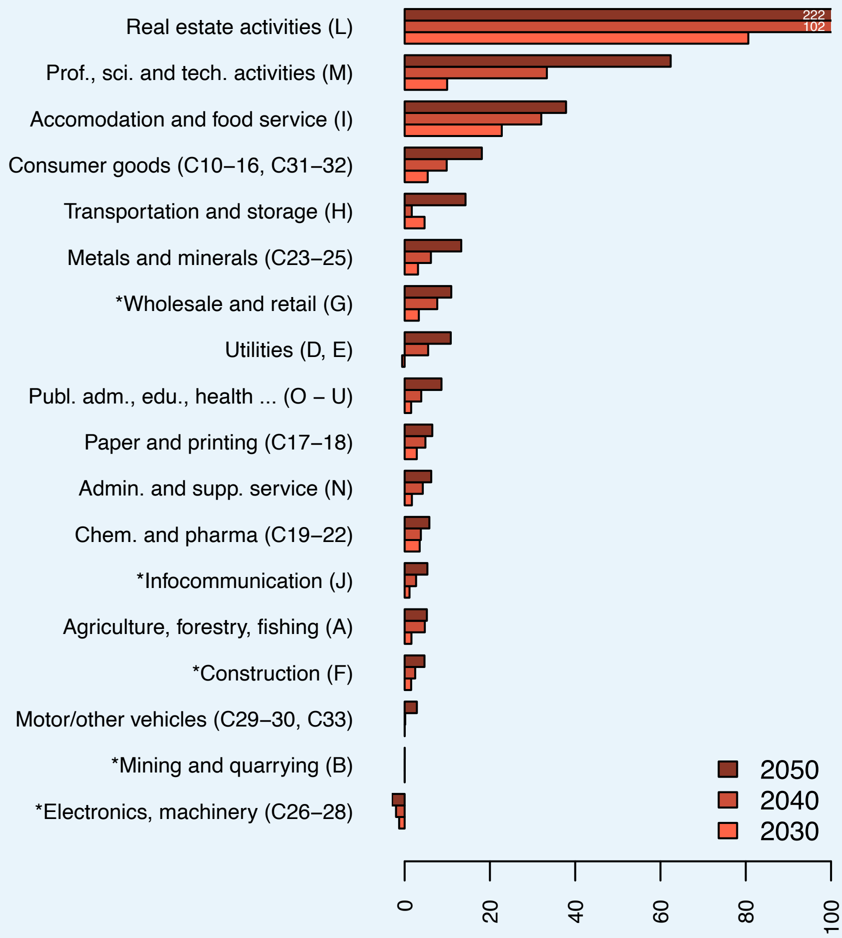
Figure 5
Excess NPL ratios
[2020 Q1 - 2050 Q4, percentage point difference from OT]



Legend: Red - FT, Yellow – DT

Notes: GVA gap and thus displayed differences are statistically insignificant for the asterisked sectors (α=0.05). Values of DE, F, and H may be influenced by multicollinearity (VIF>10).

Figure 6
Excess amount of non-performing loans in failed transition
[Billion HUF, assuming static 2019 Q4 loan amounts]



Note: Values of asterisked sectors are statistically insignificant (α=0.05).

At the national level, the total excess value at the end of 2050 is roughly half a trillion HUF. Note, however, that this is a severe underestimation since loan amounts were assumed to be static while GVAs were not. By dynamizing sectoral loan amounts with the underlying sectoral GVA growths, i.e. assuming that the loan-to-GVA ratios remain constant, the total value is about a third higher. Note that it implies a conflux of higher GVAs and thus larger loans with lower NPL ratios of orderly transition and lower GVAs and thus smaller loans with higher NPL ratios of failed transition.

6 Conclusions

With complex large-scale models, the physical consequences of climate change can be converted into economic numbers, just as the consequences of transition policies. In the context of three scenarios, I have analysed the sources of potential threats for the banking system. Sectoral debt payment abilities are widely scattered if comparing orderly and failed transition of the Hungarian (and global) economy. Disorderly transition due to late pricing of climate risks avoids harsh outcomes, but it also has permanent negative consequences for a few activities.

These results do not in any way imply that sectors with higher excess risk should not be lent. They indicate that banks should be aware of such or, as conditions change, very different prospects. In general, they advocate the incorporation of climate-awareness into banks' long-term risk management.

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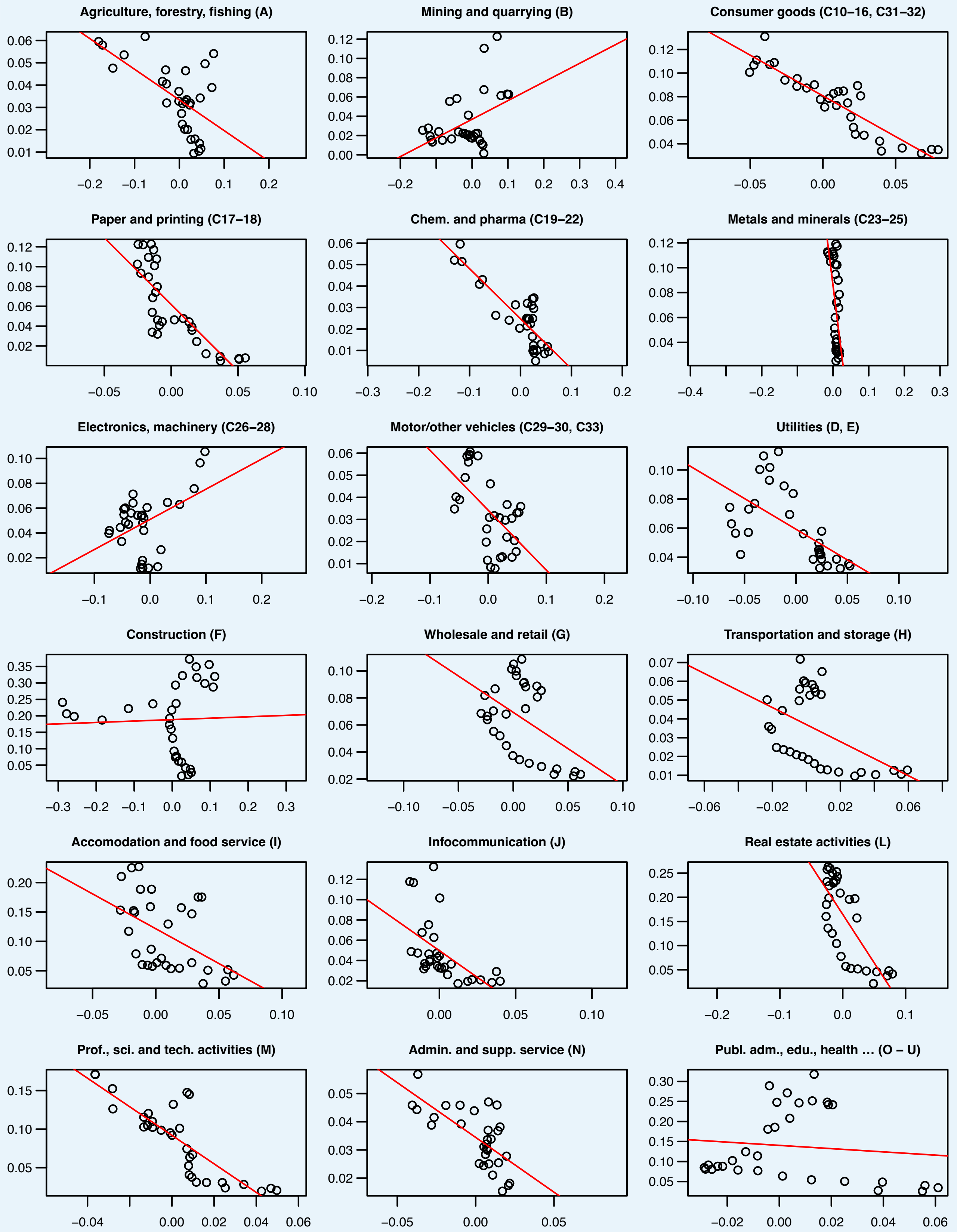
Appendix

Figure A1
Relationship between NPL (y) and GVAgap (x)



Notes: Red line depicts the two-variable regression. Scales are in decimal format.

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