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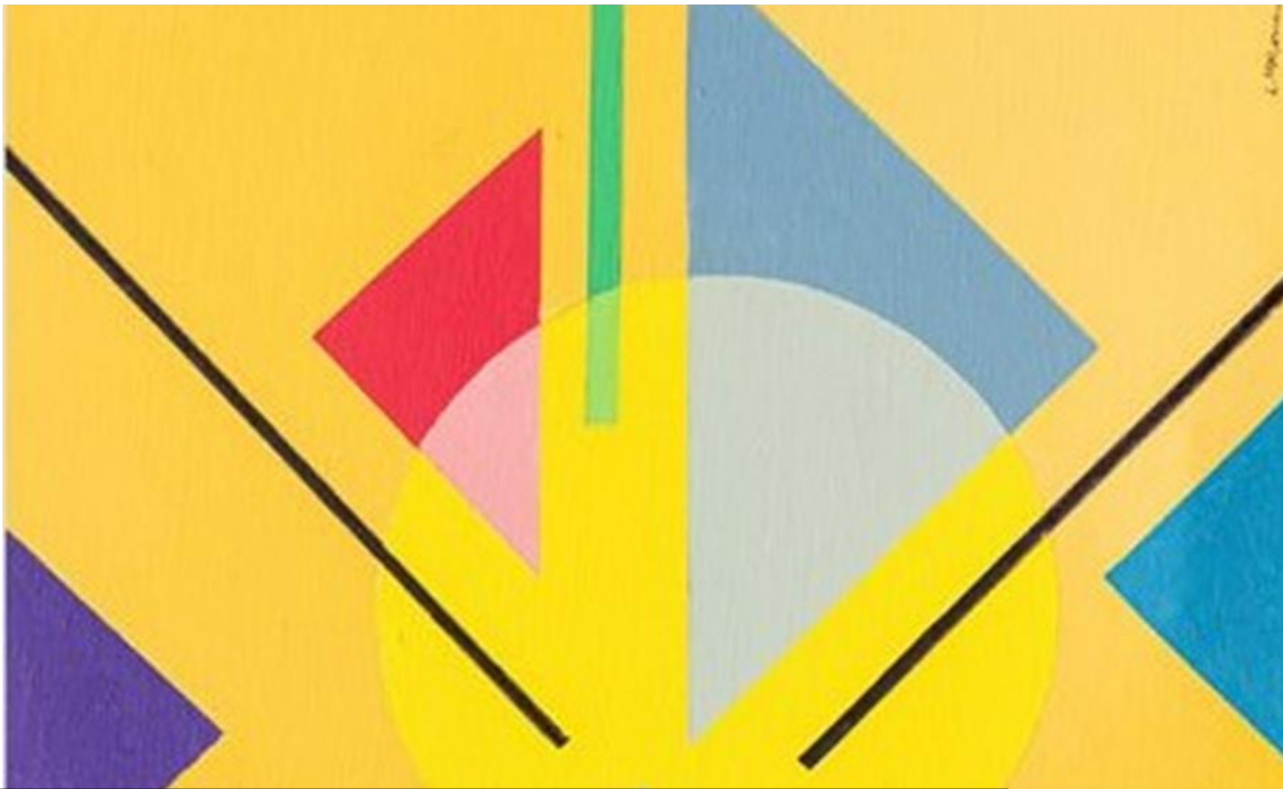

Introducing Sectoral PD Satellite Models through Constrained BACE

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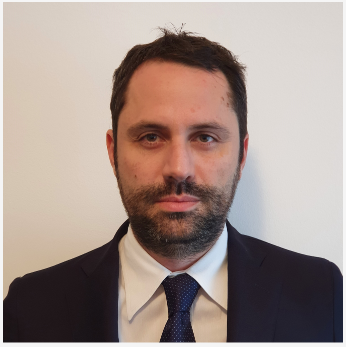
Executive Summary

In this paper we propose a methodology to estimate sectoral PD Satellite Models that can be consistently used to perform scenario analysis based on sector specific shocks. In particular, we complement the Bayesian averaging estimation approach known as BACE, with a study of the relative importance of the estimators in terms of Dominance Analysis. The final aim is to estimate models with sufficient sensitivity to the sectoral scenario driver, identified with the Gross Value Added (GVA). We end up with a methodology to produce native sectoral PD models, without having to deal with external models overlays and based on an algorithmic and easily maintainable calibration procedure. The faithful representation of the sectoral scenario narrative is managed through a customizable parametrization of the choice of models that are involved in the averaging process. Our methodological set up is particularly suited for any kind of sectoral analysis involving GVA scenarios, for instance in the case of EBA EU-wide and Climate Stress Test exercises.

About the Authors



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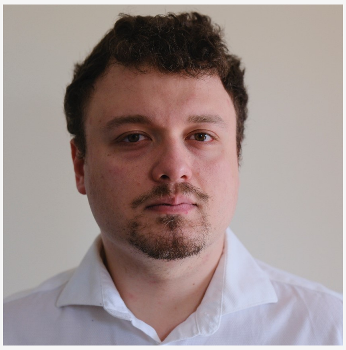

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Introducing Sectoral PD Satellite Models through Constrained BACE

Andrea Mauri Raffaele Di Sivo Riccardo Greco

Sectoral stress testing is an essential component of modern risk management and it is a vital tool used by financial institutions and regulators to assess the resilience of specific sectors of the economy or financial system under adverse conditions. This approach helps in identifying vulnerabilities within particular sectors, enabling stakeholders to implement measures to mitigate potential risks. Unlike traditional stress tests, sectoral stress tests concentrate on the collective performance of entities within a particular sector by introducing sector specific shocks, thus providing a more granular understanding of risks.

During the past few years, scenario analysis based on sectoral shocks have been progressively combined with the standard stress test exercises. There have been two main areas of application that required a specific sectoral analysis: Climate Stress Testing (starting from ECB 2022 bottom-up exercise) and EBA EU-wide Stress Tests (e.g. Covid-19 pandemic projections during 2021 exercise, sectoral scenarios and energy intensive sector classification in 2023). In this context, it is becoming increasingly important to develop statistical tools that are able to fully capture, together with general trend set by macroeconomic variables, the narrative underlining the sectoral nature of the scenarios. This introduces a new layer of complications in model estimation that includes availability of sufficiently granular data, potential lack of sensitivity of the models to the sectoral drivers, need of flexibility in the methodology to meet the different use cases and efficient model design in order to produce a set-up that can be consistently maintained.

In this paper we address the problem of sectoral scenario analysis by focusing on credit risk parameters and considering the case of estimation of PD satellite models. The main approaches currently used to introduce sectoral differentiation into PD satellite models can be essentially summarized into two main categories:

- **Overlay models**: non-sectoral models are first developed, leveraging on standard macroeconomic explanatory variables. Sectoral differentiation is introduced as an overlay coming from a second set of independent models, that produces corrections to be applied on top of the main non-sectoral impacts.
- **Native sectoral models**: models directly depend on sectoral explanatory variables together with other macroeconomic drivers and are thus able to perform sectoral scenario analysis without the introduction of further add-ons.

The two approaches can be practically introduced with a vast spectrum of variants, but generally speaking we can identify some common advantages/disadvantages. Overlay models usually provide a better control on the general trend of the macro scenario and the intensity of the overlays can be calibrated to produce a faithful representation of the sectoral narrative. As a drawback, this approach introduces two set of independent models, making it difficult to justify their methodological coherence and giving rise to a framework that is more cumbersome to be maintained. Native sectoral models overcome possible methodological inconsistencies due to the presence of multiple models and since they rely on a unique framework are naturally easier to be maintained. On the

other hand, in this case it may be more difficult to estimate models whose sensitivity properly capture the sectoral drivers, giving rise potentially to a poor sectoral differentiation.
In this paper we introduce a methodology to estimate sectoral PD Satellite model following the native sectoral modeling approach discussed above. In particular we refer to the Bayesian estimation approach known as BACE, where one samples the model space and takes an average projection weighting the sampled models in terms of a penalized likelihood [4]. This approach has several advantages with respect to other methodologies (for a critical review see [9]) and has already been applied for the estimation of PD and LGD Satellite Models implemented in iason proprietary solution *G-RiskPar* [8] [10] [11].
Since we would like to apply the methodology to perform sectoral scenario analysis, we complement the original modeling approach with a study of the relative importance of the estimators in terms of Dominance Analysis (for a review see [1]). The final aim is to estimate models with sufficient sensitivity to the sectoral scenario driver, identified with the Gross Value Added (GVA). We end up with a methodology to produce native sectoral PD models, without having to deal with external models overlays and based on an algorithmic and easily maintainable calibration procedure. The faithful representation of the sectoral scenario narrative is managed through a customizable parametrization of the choice of models that are involved in the averaging process.
Our methodological set-up is particularly suited for any kind of sectoral analysis involving GVA scenarios, for instance in the case of EBA EU-wide and Climate Stress Test exercises. A dedicated discussion is needed for the case of climate stress testing, since the regulator requires the introduction of information also at level of single counterparties [5]. Models in a climate stress test capture two main type of impacts:

- **Indirect impacts:** models that transmit climate shocks to parameters through climate-related macroeconomic variables (e.g., RRE, CRE, and GVA) connected to the sector relevant to the counterparty.
- **Direct impacts:** Models that utilize specific variables (e.g., energy consumption, water consumption, GHG emissions, carbon price, Carbon/GHG emissions intensity, EPC labels), referred to as climate-related transition variables.

From a methodological standpoint, direct impact models are more precise and accurate in determining the climate shock, but they are extremely complex to implement as they require a highly granular and detailed database for each counterparty. Conversely, while indirect impact models are easier to implement, relying on the simple introduction of a macroeconomic variable into the pool of classical regressors, they suffer from limitations in transmitting shocks. It is important to stress that our approach can be consistently used to capture the indirect impact of climate scenarios, whereas direct impact inevitably needs an analysis at the level of single counterparties which is outside the scope of this paper.
The paper is organized as follows. We start with a brief methodological introduction in Section 1, reviewing the main aspects of BACE methodology and Dominance Analysis. In Section 2 we provide details on the calibration process, including information on input data sources and final models granularity. In Section 3, we discuss in details the role of the dominance threshold and use our models to simulate an EBA-like stress exercise. Final considerations can be found in Section 4.

1. Methodological Overview

As already mentioned in the Introduction, the main issue with methodologies based on native sectoral models is given by the fact that the models combine sector specific macroeconomic variables with traditional macrovariables, risking insufficient explanation of default probability trends by the former, as most variability might be captured by other macroeconomic factors. This issue is further pronounced in a Bayesian model averaging approach, where algorithmic selection naturally assigns greater weight to variables that provide more explanatory power, thereby marginalizing variables that do not significantly explain the variability of the dependent variable. In order to describe how we tackle this problem, it is necessary first to explain how the BACE methodology works and then to outline the constraints introduced to ensure that sectoral variables play a decisive role, thereby addressing the problem of the explanatory power of individual variables on the predictive capacity of the model. They key contact between the BACE methodology and the Dominance Analysis (DA) will be deeply investigated.

1.1 BACE Estimation Approach: a Quick Review

The BACE methodology was firstly introduced by Dopphefeller, Miller e Sala-i-Martin [4]. In the context of Satellite Models estimation, we developed a proprietary algorithm [11] based on three main steps that we review here, with a central focus on BACE methodology. Briefly, the purpose of the algorithm is to avoid expert judgement, often used to estimate satellite models, aiming to preserve a statistically sound model selection phase. Moreover, the algorithmic nature of the model estimation and model selection processes allows to consistently estimate a large number of models, thus addressing the increasing need for more granular risk identification. The algorithm schematically operates as follows:

A) For each counterparty type, a list of relevant macroeconomic explanatory variable is identified. The expected impact of each macro variable on the PD (in terms of economic sign) is also determined, leading to a final list of N independent variables together with (possible) constraints on the signs.

B) A total of M OLS regression models are estimated by considering all possible combinations of k independent regressors, chosen from our initial pool of N macrovariables. Hence:

$$M = \sum_{k=1}^{K} \frac{N!}{(N-k)!k!}. \tag{1}$$

C) After excluding certain models based on the assumptions we made in the step **A)** and by leveraging on statistical criteria, the core of the BACE methodology is applied by averaging model coefficients using weights proportional to the posterior distribution of each individual model, having the following functional form:

$$P(M_j \mid y) = \frac{P(M_j)T^{-k_j/2}\mathrm{RSS}_j^{-T_j/2}}{\sum_{i=1}^{M} P(M_i)T^{-k_i/2}\mathrm{RSS}_i^{-T_i/2}}, \tag{2}$$

where M_j identifies the j-th model with $j \in [1, M]$, y is the the dependent variable vector, $P(M_j)$ is the prior probability of the j-th model, T_j is the number of observation used for the j-th model, k_j is the number of independent variables, and finally RRS_j identifies the Residual Sum of Squares of the j-th model. A distinctive feature of BACE methodology is that, unlike classical Bayesian-averaged models, the *a priori* probability weight of the j-th model is fixed as uniform ($\frac{k}{N}$) and thus cancels out from Equation (2) and the models is free of its weight. After the posterior probability is computed, it is used to estimate the posterior coefficient for each single variable involved in the modelling phase:

$$E(\beta_i|y) = \sum_{j=1}^{M} P(M_j|y)\hat{\beta}_{i,j}, \tag{3}$$

where $\hat{\beta}_{i,j}$ is the i-th OLS estimation of the j-th model and $j \in J_M$ where J_M is M subset composed by those models where the i-th estimate is present.

From Equation (2) and fixing the *a priori* probability as uniform, we can deduce that the posterior probability is a useful metric for understanding the explanatory power of a variable within the model. The greater the weight we give to an estimated coefficient, the larger its impact in explaining the variability of the final model.

1.2 C-BACE: Dominance Analysis Constraint

Dominance Analysis (DA) is a method used in multiple regression to compare the relative importance of predictors by examining all possible subset models that could be obtained with a different combination of the same regressors [1]. This approach helps in understanding how different predictors contribute to the prediction of the independent variable, providing a detailed view of predictors importance. In general, when discussing DA, one can usually refer to:

- *Complete Dominance*: a predictor X_i completely dominates another predictor X_j (with $i \neq j$) if X_i adds more unique variance than X_j across all subset models. This means X_i consistently shows higher importance in every possible model where both predictors are included.
- *Conditional Dominance*: a predictor X_i conditionally dominates another predictor X_j (with $i \neq j$) if X_i has a greater average additional contribution to the model fit compared to X_j within each subset size. Conditional dominance is assessed by comparing predictors within models of the same size.
- *General Dominance*: a predictor X_i generally dominates another predictor X_j (with $i \neq j$) if the average additional contribution of X_i across all subset models is greater than that of X_j. This measure averages the importance of X_i over all possible models.

In this research, we use the conditional dominance approach to calculate the relative importance percentages of the regressors involved in the BACE estimation process. The following steps are followed:

1. *Fit All Subset Models*: generate all possible subset models of the predictors. For k predictors, this involves fitting 2^k models;
2. *Calculate R^2 Values*: for each subset model, compute the proportion of variance in the criterion variable Y explained by the predictors in the model (R^2);
3. *Compute Additional Contributions*: for each predictor, calculate its additional contribution to R^2 by comparing models that include the predictor to those that do not;
4. *Averaging Contributions*: calculate the average additional contribution for each predictor within each subset size;
5. *Relative Importance*: The relative importance percentage for each predictor can be derived by comparing their contributions. For instance if predictor X_i has a general dominance measure of 0.30 and the total R^2 for the full model is 0.60, then the relative importance of X_i is $\frac{0.30}{0.60} \times 100 = 50\%$.

In order to let the posterior probability be a good proxy of the weight that the variable has in the final model, it must be calculated over the entire pool of models that are subject to averaging. At this level, constraints can be applied on the pool of models as already mentioned in the previous Section at Step **C)**. In particular, our algorithm excludes from the calculation of the Bayesian mean all those models that display wrong economical signs (e.g. a positive sign for GDP for PD models) and are not statistically consistent (e.g. violate OLS assumptions).
At this stage, we introduce a new step (between B and C) within the above algorithm, specifying more about the models that will have to feed BACE:

B.2) For each of the j-th estimated models a conditional DA is performed, which estimates a relative importance index for each variable in the estimated model. Only those models that contain a GVA with a relative percentage importance greater than a given cut-off will feed into the final pool of models on which to average.

Therefore, we end up with a methodological approach that depends only on two hyperparameters, that the user can choose to calibrate:

- The **number k** of regressors contained into each OLS models. This should be related to the depth of the independent variable time series, in order to avoid overfitting;

- The **cutoff** z, that we use to identify models for which the added value can significantly explain the variability of the model. It should be set in such a way as to balance the sensitivity with respect to value added and the possible drop of performance in terms of R^2 of the final model.

2. Model Calibration

We now apply the methodological framework described in Section 1 to estimate PD sectoral satellite models. We start by introducing details about the input data for model calibration, for both target and explanatory variables (see sections 2.1 and 2.2 respectively). We also specify the choice made for the free hyperparameters of the methodology in section 2.3.

2.1 Target Variables

As a proxy for modeling PDs, we use decay rates time series provided by Bank of Italy[1]. In particular, we select two counterparty types for which sectoral decomposition is relevant, namely Italian Non Financial Corporates (NFC) and Italian Producer Households (HP). The time series span quarterly from 2000q4 to 2022q4 and we estimate models with both geographical and sectoral breakdown (for the full list of models implemented in our solution see Appendix B). As a technical note, the target time series have been transformed by logit function to avoid domain issues.
In this paper, we choose to illustrate our results by considering examples for the full italian geography without further breakdown and for the "Manufacture of basic metals" (C24-C25) NACE sector. At first, we use the NFC model to conduct a sensitivity analysis on the GVA variable in order to capture the effect of an increasing dominance cutoff z. Secondly, we use the HP model of the same industry sector as en example to analyze the impact of a predefined macroeconomic scenario on the PDs, by simulating an EBA-like stress exercise. The above models are chosen among the full list of estimated models of Appendix B, because the general pattern under DA threshold variations is particularly manifest, making them good examples for illustrative purpose.

2.2 Set of Macrovariables

The explanatory variables involved in the estimation of PD satellite models are selected on the basis of the available literature on the topic [7][3]. We source the data from publicly available standard data providers (Istat, Banca d'Italia, European Central Bank, Euribor). In particular, we leverage on the following set of independent variables:

- *Classical macrovariables*: Gross Domestic Product (GDP), 10year-bond, brent oil price, unemployment rate, EUR FX, FTSE MIB Index, house price index, italian-german spread;
- *Sectoral drivers*: gross value added for each NACE sector. It represents the share of GDP produced by the sector to which the GVA belongs.

Each regressor is a quarterly time series and it is considered with 0, 1, 2 and 3 lags. In order to ensure the stationarity of regressors, avoiding the case of spurious regression, we transformed the macrovariables using the quarterly annual variation formula:

$$y_t = \sum_{i=1}^{4} \frac{x_t - x_{t-i}}{x_t}. \tag{4}$$

2.3 Model Estimation

After input data elaboration, we estimate the models following the methodological steps that have been fully detailed in Section 1. As already mentioned, the methodology depends on two customizable hyperparameters, that we set as follows:

[1] Banca d'Italia - Base dati statistica.

cona	co10	co30	co40	co50
0.066%	1.267%	1.828%	2.054%	3.339%

TABLE 1: Sector C24-C25, yearly estimated sensitivity projections under different DA cutoffs

cona	co10	co30	co40	co50
0.054%	0.824%	1.538%	2.154%	3.157%

TABLE 2: Sector averaged italian NFC models sensitivities under different DA cutoffs

cona	co10	co30	co40	co50
89.187%	88.445%	87.629%	87.322%	87.283%

TABLE 3: Sector C24-C25 NFC, R^2 values under different DA cutoffs

cona	co10	co30	co40	co50
76.661%	75.135%	72.160%	70.201%	69.539%

TABLE 4: Italian NFC models, averaged R^2 values under different DA cutoffs

- *Cutoff k*: compatibly with the length of input time series, we choose to set k equals to 5 for NFC and a k equals to 6 for the HP targets;
- *Cutoff z*: in order to fully capture the effect of this parameter, we decide to compare the results for a span of different values (no-cutoff, 0.1, 0.3, 0.4, 0.5).

We end up with a total of 261 PD satellite models for the NFC and HP counterparties, differentiated by NACE sector and geography as reported in Appendix B.

3. Case Study

In this Section we use the models selected in Section 2.1 as examples to test our methodology from different perspectives. Since the DA threshold parameter z plays a central role in our construction, in Section 3.1 we first study the effect of its variation on the final models GVA sensitivity and on the overall performance. In Section 3.2, we finally test the model application to a full EBA-like scenario, highlighting the effect of different DA cutoff choices.

3.1 Comparison of Models Estimation with Progressive Dominance Threshold

We perform a sensitivity analysis on the GVA over a three year projection scenario (2023-2025) based on the following assumptions: we keep all the macrovariables fixed to the starting date value except for the GVA, for which we consider a first scenario with baseline variations (BL) over the three years and a second scenario (stressed scenario, ST) with an Year-on-Year one percentage change (-Δ1%) of the GVA with respect to the baseline (BL). This allows to isolate the specific sectoral GVA effect on the forecasts, subject to progressive DA cutoffs.
The sensitivity analysis is performed at first for the "Manufacture of basic metals" sector (NACE ID: C24-C25) beloging to NFC counterparties. Macrovariables values at reference date (2022q4) are taken from actual data from the Economic Bulletin No. 4, 2023 by the Bank of Italy (BoI) [2].
In Table 1 we report the annualized sensitivities (S), given as relative variations of the PDs of the stressed scenario with respect to the baseline, that we choose to compute for the last year of projection (2025):

$$S(t) = \frac{PD_{ST}(t)}{PD_{BL}(t)} - 1. \tag{5}$$

	Unemployment Rate	GVA C24-25	House Price Index
2023	6.00%	1.10%	3.60%
2024	4.00%	1.30%	1.70%
2025	4.50%	1.30%	1.00%

TABLE 5: Baseline Scenario. Unemployment rates are expressed as levels while GVA and HPI scenarios are provided as year-on-year variations

	Unemployment Rate	GVA C24-25	House Price Index
2023	9.00%	-4.90%	-3.50%
2024	12.00%	-12.40%	-3.10%
2025	14.00%	1.40%	-2.50%

TABLE 6: Adverse Scenario. Unemployment rates are expressed as levels while GVA and HPI scenarios are provided as year-on-year variations

	cona	co10	co30	co40	co50
2023	3.440%	3.040%	4.819%	4.015%	0.132%
2024	23.335%	22.186%	21.731%	16.058%	2.523%
2025	50.486%	42.867%	34.537%	24.354%	5.016%

TABLE 7: Sector C24-C25 HP, Baseline-Adverse discriminatory power projections under different DA cutoffs

	cona	co10	co30	co40	co50
2023	3.875%	2.655%	1.574%	1.212%	0.879%
2024	43.175%	37.563%	22.611%	13.118%	1.202%
2025	92.538%	90.231%	46.273%	21.811%	2.782%

TABLE 8: Italian HP models, sector averaged discriminatory power projections under different DA cutoffs

The tabulated data reveal a clear increase in the sensitivity by increasing the DA cutoff.
As highlighted in the Table 2, the same pattern-like feature is observed by calculating the average sensitivity across all the NACE sectors on the full list of NFC models of Appendix B.

This finding is not unexpected, given the direct relation between the relative importance of regressors and the value of the final model coefficients. Indeed, variables with higher relative importance translate into a higher absolute value of the variables' coefficients, influencing the explanation of the data variability. Therefore, the final estimates of the BACE coefficients are affected both in the posterior probabilities of the model and in the value of the estimated coefficients.
It is important to understand how the different DA thresholds impact the performance of the models. We use R^2 to quantify goodness of fit and report the results for the C24-C25 sector model under different cutoff values in Table 3. As manifest in this Table, in general the model performance slightly decreases as the Dominance threshold is increased. This behavior can be explained in terms of the bias introduced in the coefficients' estimates by the threshold. Hence, the cut-off must be calibrated considering the trade-off between an increasing sensitivity to GVA scenario variations and a deterioration in the overall model fit.

The same decreasing pattern for the performance is present for all the NFC models, as shown in Table 4. For each specific cutoff, the displayed R^2 values are calculated by averaging the R^2 values over the full set of sectoral models.

cona	co10	co30	co40	co50
62.03%	60.07%	58.30%	55.83%	54.11%

TABLE 9: Sector C24-C25, R^2 values under different DA cutoffs

cona	co10	co30	co40	co50
61.07%	59.56%	56.36%	55.80%	54.13%

TABLE 10: Italian HP models, averaged R^2 values under different DA cutoffs

3.2 Scenario Analysis on EBA like Stress Exercise

In the previous section a sensitivity analysis with respect to the sectoral driver (GVA) has been performed. We would like now to test our models against a fully fledged three years macroscenario, to analyze the effects of the Dominance procedure on a real-case stress test simulation. For this exercise, the BL scenario is provided by the Economic Bulletin No. 4 of the BoI [2], whereas the Adverse scenario is partially derived from the EBA 2023 Stress Test Exercise [6]. Some relevant variables for the Baseline scenario are reported in Table 5, while the corresponding Adverse scenario variables are reported in Table 6. In particular, the sectoral evolution driver (GVA) is precisely taken from the EBA 2023 Stress Test Exercise input shocks [6].
As mentioned in Section 2.1, the model for italian HP counterparties and industrial sector "Manufacture of basic metals" sector (C24-C25), is used as a benchmark to process the full scenario. Once again, in analogy with Equation 5, we compute the Adverse vs Baseline PDs relative variations and report them in Table 7. From this Table, it is apparent that the discriminating power between adverse and baseline scenario of the models decreases with the increase of the cutoff. This pattern is due to the fact that in general for increasing DA thresholds, while the added value coefficient is forced to be more important in the model variance explainability, the overall sensitivity to the other explanatory variable is is progressively dumped. Consequently, the stress levels in the final projections will shift from the low-cutoff to the high-cutoff condition, where only the sectoral added value variable exhibit a significant influence.
Again, the same pattern is replicated for the whole set of HP models. Table 8 shows the overall year-by-year/cutoff discriminatory power between *baseline* and *adverse* scenarios averaged over all the sectors. From this analysis, it is clear that too high values for DA threshold can badly affect the out of sample behaviour of the model and the calibration of the parameter must yield sufficient discriminatory power to the final model.
For completeness, we replicate here the performance test of the previous Section for the C24-C25 model (Table 9) and for the sector averaged HP models (Table 10).
The behaviour for the performance indicator is in line with the one displayed for the Non Financial Corporate models introduced in the previous Section and display the same decreasing pattern with increasing cutoff values.

4. Conclusions

In this paper we introduced a framework to estimate sectoral PD satellite models, based on a native sectoral methodology that combines Bayesian averaging with Dominance Analysis. The main advantage of the methodology resides in its algorithmic nature, that allows for automatic estimation and model selection procedures governed by two customizable hyperparameters. In particular, the practitioner can calibrate manually model sensitivity to selected drivers, introducing domain expert consideration in such a way as to preserve a statistically sound estimation procedure and avoiding the manual choice of a single model out of all the possible consistent candidates. The final models display a good trade-off between performance and sectoral sensitivity, making them particularly suited for Stress Test Exercises driven by GVA scenarios. It would be interesting to extend the analysis of this paper by considering other sectoral drivers, with the definition of an automatic multi-cutoff calibration procedure.

References

[1] **Azan, R. and Budescu, D.V.** *The Dominance Analysis Approach for Comparing Predictors in Multiple Regression*. Psychological Methods, June 2003.

[2] **Banca D'Italia.** *Economic Bulletin Number 4.* October 2023.

[3] **Dees, S., Henry, J. and Martin, R.** *STAMP€: Stress-Test Analytics for Macroprudential Purposes in the euro area*. ECB Research and Publications, 2017.

[4] **Doppelhofer, G., Miller, R.I. and Sala-i-Martin, X.** *Determinants of long-term growth: A Bayesian averaging of classical estimates (BACE) approach*. American Economic Review, Vol. 94, Issue n.4. 2004.

[5] **European Central Bank.** *ECB report on good practices for climate stress testing*. 2022.

[6] **European Central Bank.** *2023 stress test of euro area banks.* July 2023.

[7] **Figlewski, Frydman, H. and Liang, W.** *Modeling the effect of macroeconomic factors on corporate default and credit rating transitions*International Review of Economics & Finance, Vol. 21, n. 1, 2012.

[8] **Mauri, A., Di Sivo, R., Veksin, E.** *LGD Stress Testing: a Bayesian Averaging Modeling Approach*. Research Paper Series, Issue n. 60, Sep 2023.

[9] **Mauri, A., Rubicondo, D., Ferretti, T., Polino N. and Rogante, N.** *Advancements in Bank Stress Tests: from Bayesian Averaging to Causal AI*. Research Paper Series, Issue n. 53, March 2023.

[10] **Scaravaggi, A. and Stucchi,E.** *A Benchmark Framework for IFRS9 Multiyear-PD Curves Estimation and Stress Testing Exercise: an Application*. Research Paper Series, Issue n. 14, April 2019.

5. Sitography

[11] **Iason ltd.** *Current solutions' portfolio.*

A. *Annex*

B. Full List of Models

We describe here the granularity of our full set of PD models for the NFC and HP counterparties. At level of industry breakdown, we have considered the list of NACE sectors reported in Table 11. At level of geographical breakdown, we estimate the Italian national model; five macro-areas models (North-western Italy, North-eastern Italy, Central Italy, Southern Italy, Insular Italy); twenty Italian regions models.

NACE Sectors
Accommodation and food service activities
Administrative and support service activities
Air transport
Construction
Crop and animal production, hunting and related service activities
Electricity, gas, steam and air conditioning supply
Financial and insurance activities
Forestry and logging
Land transport and transport via pipelines
Manufacture of basic metals
Manufacture of basic pharmaceutical products and pharmaceutical preparations
Manufacture of chemicals and chemical products
Manufacture of computer, electronic and optical products
Manufacture of food products, beverages and tobacco products
Manufacture of furniture
Manufacture of motor vehicles, trailers and semi-trailers
Manufacture of other non-metallic mineral products
Manufacture of textiles
Mining and quarrying
Other sectors net of U
Professional, scientific and technical activities
Real estate activities
Telecommunications
Warehousing and support activities for transportation
Water collection, treatment and supply
Water transport
Wholesale and retail trade and repair of motor vehicles and motorcycles

TABLE 11: *NACE sector list*