
EUROPEAN
DATAWAREHOUSE

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IRISH SECURITISATION EVENT

12 MAY 2026

AGENDA

WELCOME & INTRODUCTION
DR. CHRISTIAN THUN (EDW)

REGULATION IN FOCUS
DR. CHRISTIAN THUN (EDW)

FIRESIDE CHAT: CAPITAL CLIFFS & EU SECURITISATION REGULATIONS
GEORGES DUPONCHEELE (GREAT LAKES INSURANCE SE),

FRONTIER MODELLING BEST PRACTICES: LEVERAGING EDW DATA TO BOOST PERFORMANCE IN FINANCIAL RISK MODELS
TOMMASO GUERRINI (CARDO AI)

DEALDOX®: A DATA ROOM FOR SECURITISATION
SAMUEL STANIS (EDW)

PANEL: WHAT'S NEW? ABS STRUCTURED FINANCE
MODERATOR: MARTIN KUHN (EDW), MICHAEL OSSWALD (SVI), CLAIRE MCKENNA (TMF), MARK WEEDON (ONATE), VALERIE O'FLAHERTY (EURONEXT DUBLIN)

CLOSING REMARKS

NETWORKING RECEPTION

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WELCOME & INTRODUCTION

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REGULATION IN FOCUS

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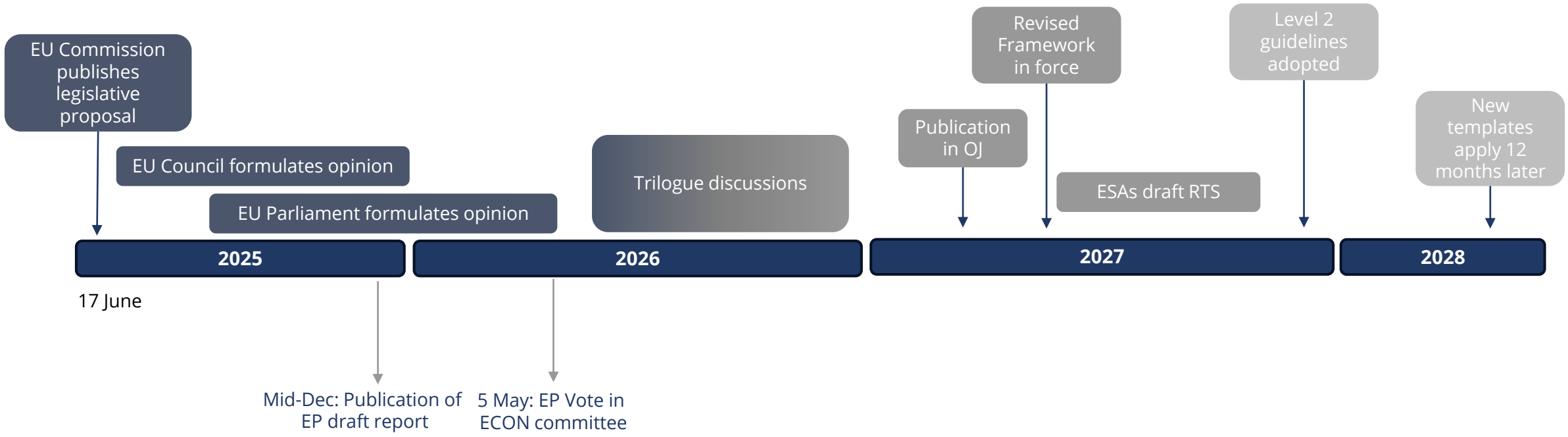
COMPARISON OF POSITIONS ON TRANSPARENCY

	EU Commission (17 June 2025)	EU Council (12 Dec 2025)	EU Parliament (5 May 2026)

Public vs. private	• Public securitisation is defined by meeting any of the following:
	  • a prospectus has been drawn up
	  • securitisation trading on a Union trading venue
	  • terms and conditions are not negotiable
	• Private securitisation does not meet the above criteria
		• Public securitisation is where a prospectus has been drawn up pursuant to the EU prospectus regulation
		• Private securitisation is where a prospectus has been drawn up not pursuant to the EU prospectus regulation
			• Public securitisation is where a prospectus has been drawn up pursuant to the EU prospectus regulation and
			• The underlying pool of exposures is actively managed by the originator or sponsor
			• Private securitisation does not meet the above criteria

Transparency (Art 7)	• Streamlined reporting template for public securitisations • Simplified reporting template for private securitisations • Public & private securitisations should report to repositories • ABCP transaction or a securitisation of highly-granular pools of short-term exposures shall use aggregate format	• Streamlined reporting template for public securitisations • Simplified reporting template for private securitisations • Public & private securitisations should report to repositories • ABCP transaction or a securitisation of highly-granular pools of short-term exposures shall use aggregate format • Certain synthetic deals are exempt	• Streamlined reporting template for public securitisations • Simplified reporting template for private securitisations • Public & private securitisations should report to repositories • Securitisation of highly-granular pools or ABCP shall use aggregate format • Certain synthetic deals are exempt

TENTATIVE TIMELINE FOR NEW SECURITISATION FRAMEWORK



CAPITAL CLIFFS & EU SECURITIZATION REGULATIONS

GEORGES DUPONCHEELE (GREAT LAKES INSURANCE SE)

RISK CONTROL

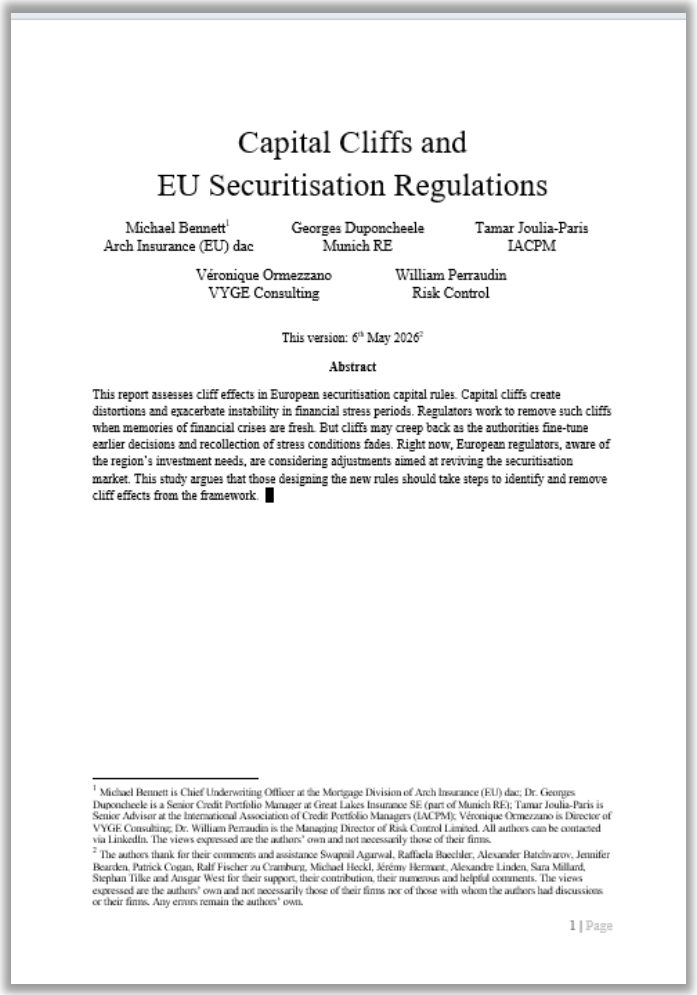
Capital Cliffs in EU Securitisation Rules

Presentation by
Georges Duponcheele, Munich RE
William Perraudin, Risk Control

May 2026

Preamble (1/2)

This talk draws on our recent report



Capital Cliffs and
EU Securitisation Regulations

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Véronique Ormezzano VYGE Consulting
William Perraudin Risk Control

This version: 6th May 2026[2]

Abstract

This report assesses cliff effects in European securitisation capital rules. Capital cliffs create distortions and exacerbate instability in financial stress periods. Regulators work to remove such cliffs when memories of financial crises are fresh. But cliffs may creep back as the authorities fine-tune earlier decisions and recollection of stress conditions fades. Right now, European regulators, aware of the region's investment needs, are considering adjustments aimed at reviving the securitisation market. This study argues that those designing the new rules should take steps to identify and remove cliff effects from the framework.

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[2] The authors thank for their comments and assistance Swapnil Agarwal, Raffaela Baechler, Alexander Batchvarov, Jennifer Bearden, Patrick Cogan, Ralf Fischer zu Cramburg, Michael Heckl, Jérémy Hermant, Alexandre Linden, Sara Millard, Stephan Tilke and Ansgar West for their support, their contribution, their numerous and helpful comments. The views expressed are the authors' own and not necessarily those of their firms nor of those with whom the authors had discussions or their firms. Any errors remain the authors' own.

But, also, on earlier papers that study the alignment of regulatory capital and risk:

Making the Bank Securitisation Capital Rules Work for Europe

What Could be Improved in the June 17th Proposals?

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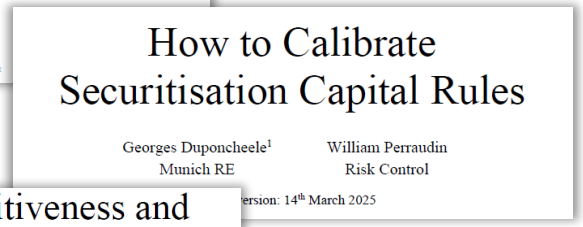
This version: 1st October 2025[2]



How to Calibrate Securitisation Capital Rules

Georges Duponcheele[1] Munich RE
William Perraudin Risk Control

ersion: 14th March 2025

European Competitiveness and Securitisation Regulations

Georges Duponcheele[1] GLISE
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William Perraudin Risk Control
Alessandro Tappi EIF

This version: 6th August 2024[2]

Rethinking the Securitisation Risk Weight Floor

Dr. Georges Duponcheele[1] Marc Fayémi Jérémy Hermant
Dr. William Perraudin Dr. Frédéric Zana
with the participation of the Paris Europlace Securitisation Committee Experts Group on Prudential Regulation[2]

This version[3]: 3rd May 2024

Preamble (2/2)

These and other studies of securitisation regulations can be found in the Insights area of the Risk Control website: www.riskcontrollimited.com

RISK CONTROL

Agenda

1. Introduction
2. Ratings-based Cliffs
3. Capital Formula Cliffs
4. Label (STS and Resilience) Cliffs
5. Unfunded risk transfer cliffs
6. Opening STS Synthetic Securitisation to Insurers Without New Cliffs
7. Funded, collateral and liquidity cliffs
8. Conclusion

RISK CONTROL

1. Introduction

- This report assesses cliff effects in European securitisation capital rules.
  - Capital cliffs create distortions and exacerbate instability in financial stress periods.
  - Regulators work to remove such cliffs when memories of financial crises are fresh.
  - But cliffs may creep back as the authorities fine-tune earlier decisions and recollection of stress conditions fades.

- Right now, European regulators, aware of the region's investment needs, are considering adjustments aimed at reviving the securitisation market. This study argues that those designing the new rules should take steps to identify and remove cliff effects from the framework.

Capital Cliffs Definition
Capital cliffs cause large jumps in capital requirements from small changes in risk or regulation, impacting financial stability during stress.

Impact on Banking Sector
Abrupt capital shocks force banks to deleverage, reduce lending, and sell assets, worsening economic downturns and market liquidity.

Regulatory Challenges
Poorly designed prudential thresholds risk undermining securitisation reforms by creating cliff effects that discourage market participation.

Policy Recommendations
Reform must evaluate capital rules under stress scenarios to avoid cliffs and support financial stability and sustainable market growth.

RISK CONTROL

1. Capital Cliff Types and Examples

- We distinguish between:
  - "**static cliffs**" in which exposures that closely resemble each other in risk characteristics receive sharply different capital treatments;
  - "**dynamic cliffs**" in which variation over time in the determinants of capital levels generates discontinuous changes in capital requirements, potentially exacerbating challenges firms and regulators face in stress periods.
- We study the effect of cliffs in European securitisation capital rules, focussing on the following examples of cliffs:
  1. Ratings based cliffs
  2. Capital formula cliffs
  3. Label (STS and Resilience) cliffs
  4. Unfunded risk transfer cliffs
  5. Funded protection collateral treatment cliffs.

Behavioral Impacts

Both static and dynamic cliffs influence market behavior by encouraging deal structuring and risk avoidance around regulatory thresholds.

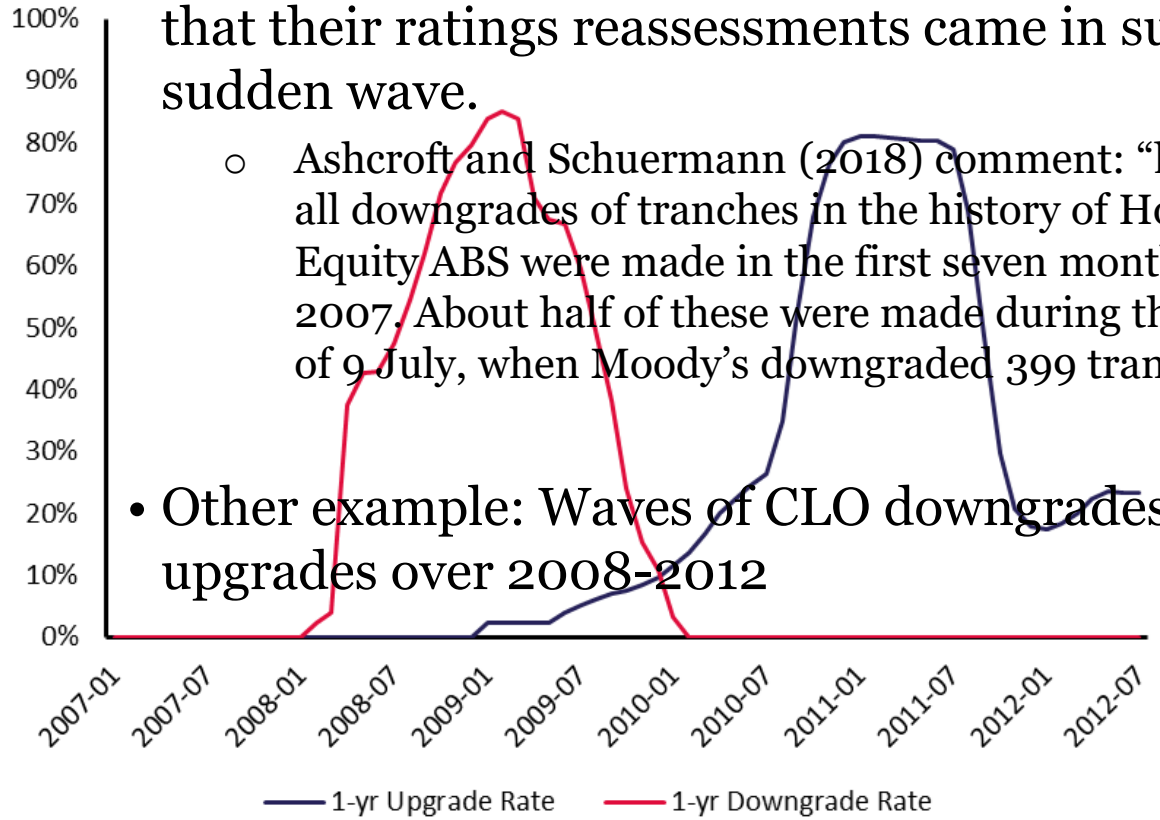
Policy Design Challenges

Effective regulations smooth transitions and limit abrupt capital changes to enhance financial stability.

RISK CONTROL

2. Ratings-based Cliffs (1/2)

- The financial turmoil and pressure on bank capital ratios in 2007 was caused not just by ratings agency inaccurate judgments but the fact that their ratings reassessments came in such a sudden wave.
    - Ashcroft and Schuermann (2018) comment: "half of all downgrades of tranches in the history of Home Equity ABS were made in the first seven months of 2007. About half of these were made during the week of 9 July, when Moody's downgraded 399 tranches.
- Other example: Waves of CLO downgrades and upgrades over 2008-2012



Moody's 1-yr downgrade and upgrade rates on global CLOs

Nature of Capital Cliffs

Capital cliffs occur when regulatory capital depends directly on external credit ratings, causing abrupt changes in requirements.

Historical Examples

During crises, rating methodology changes led to sweeping downgrades and increased capital demands on financial institutions.

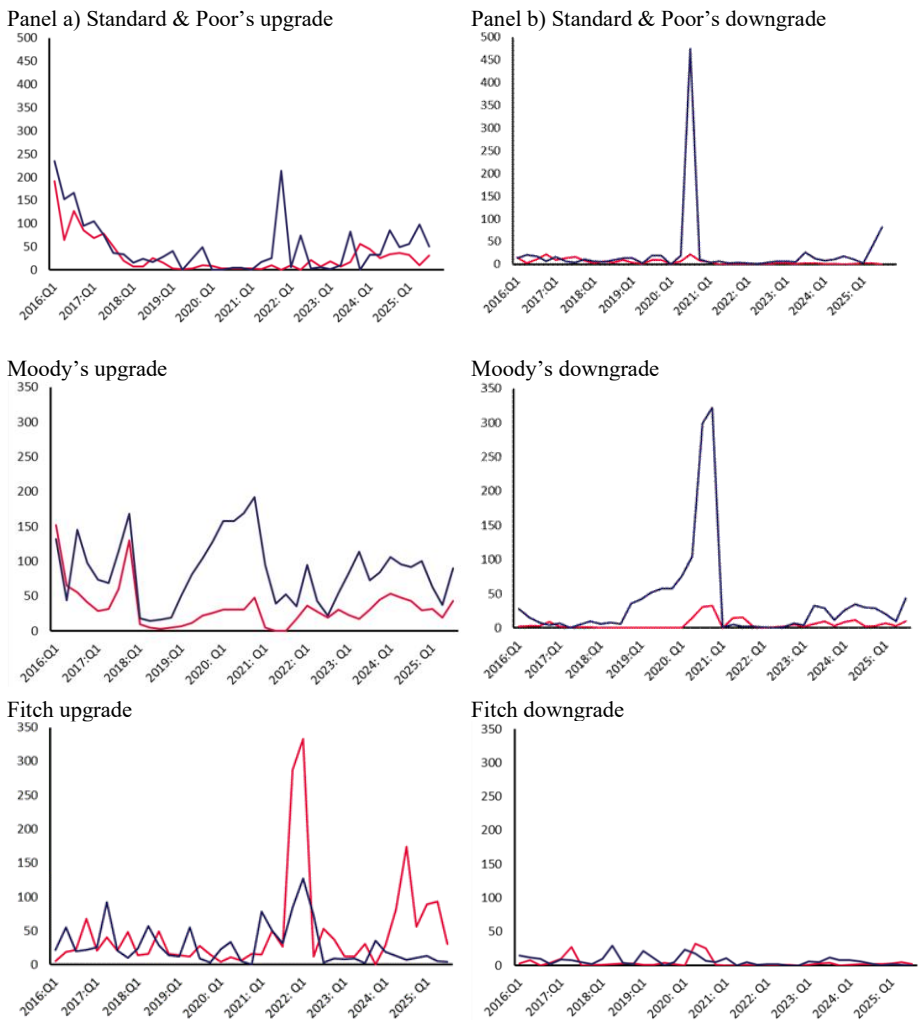
Financial Stability Risks

Rating-based cliffs can trigger simultaneous asset sales, increasing market volatility and liquidity stress.

RISK CONTROL

2. Ratings-based Cliffs (2/2)

- Other example: Waves of CLO downgrades and upgrades during **COVID** (with Moody's, S&P, but not Fitch)



The wave issue
The core problem is not that ratings change, but that they can change in a highly concentrated and non-linear manner when agencies revise methodologies or reassess entire asset classes.

Regulatory challenges
Removing ratings entirely is challenging, particularly for securitisation, where external assessments remain an important information source for investors and supervisors.

Policy Mitigation Strategies
The overarching objective is to ensure that rating actions, when they occur, translate into gradual adjustments in capital rather than destabilising shocks that undermine market confidence and financial stability.

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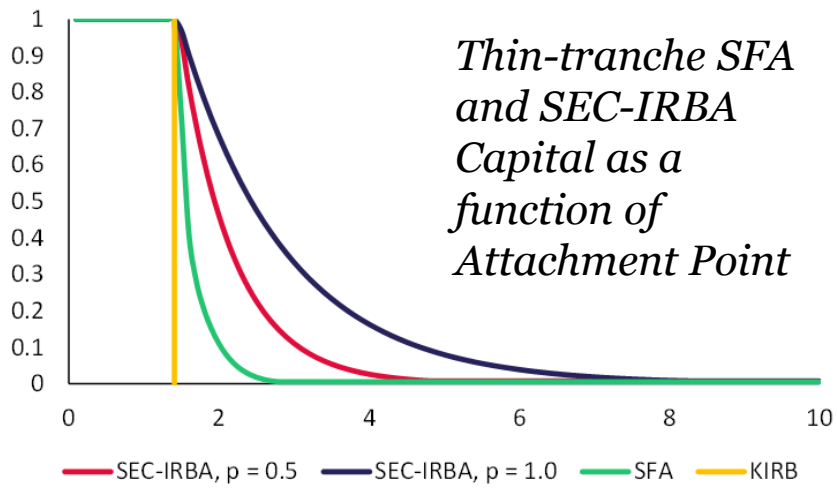
3. Capital Formula Cliffs (1/2)

- Cliff effects in securitisation which have been discussed by regulators for more than 20 years, namely those generated by the Basel II Supervisory Formula Approach (SFA) and subsequent, formula-based methods of computing securitisation regulatory capital. The SFA generated a cliff because the capital function declines sharply, as seniority increases.
- SEC-IRBA uses the p-factor to smoothen the cliff-effect.



Thin-tranche SFA and SEC-IRBA Capital as a function of Attachment Point

Capital Formula Cliffs Explained
Capital requirements sharply decline with tranche seniority creating cliff-like profiles, especially for senior tranches.

Stress Scenario Impacts
Under stress, capital needs jump substantially for senior tranches, reducing balance-sheet flexibility.

p-factor Smoothing Trade-Off
Increasing p-factor reduces cliff severity but raises total capital and non-neutrality of the framework.

Alternative Structural Solution
Scaling pool capital before formula entry shifts cliffs without increasing overall non-neutrality.

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3. Capital Formula Cliffs (2/2)

- Excessive non-neutrality can discourage securitisation altogether and undermine its role as a risk-transfer mechanism. Conversely, a low p-factor preserves capital neutrality but steepens the curve, reintroducing cliff effects.
- In stressed conditions, if pool credit quality deteriorates, pool capital increases leading to relatively senior tranches being subject to much higher capital charges (a dynamic cliff).

Current and Proposed Senior Tranche Risk Weights

Asset Type	Cases	Current		Proposed							
				Originator/Sponsor				Investor			
		STS	Non-STS	STS		Non-STS		STS		Non-STS	
				Res.	Non-Res.	Res.	Non-Res.	Res.	Non-Res.	Res.	Non-Res.
RMBS	Base case	10.00	17.73	5.00	5.00	7.00	7.00	11.29	14.39	N/A	14.39
	A-grade stress	85.24	119.09	71.70	71.70	71.70	85.24	98.78	119.09	N/A	119.09
	Ratio of A-grade stress to base case	8.52	6.72	14.34	14.34	10.24	12.18	8.75	8.28	N/A	8.28
Corporate	Base case	10.00	20.24	5.00	5.00	7.00	9.40	12.52	20.24	N/A	20.24
	A-grade stress	160.80	188.27	143.85	143.85	143.85	160.80	164.78	188.27	N/A	188.27
	Ratio of A-grade stress to base case	16.08	9.30	28.77	28.77	20.55	17.11	13.16	9.30	N/A	9.30

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4. Label (STS and Resilience) Cliffs (1/3)

Solvency II Capital Charges (Delegated Act 2015)

	Type 1							Type 2						
	AAA	AA	A	BBB	BB	B	CCC	AAA	AA	A	BBB	BB	B	CCC
Year	CQS 0	CQS 1	CQS 2	CQS 3	CQS 4	CQS 5	CQS 6	CQS 0	CQS 1	CQS 2	CQS 3	CQS 4	CQS 5	CQS 6
1	2.1	3.0	3.0	3.0				12.5	13.4	16.6	19.7	82.0	100.0	100.0
2	4.2	6.0	6.0	6.0				25.0	26.8	33.2	39.4	100.0	100.0	100.0
3	6.3	9.0	9.0	9.0				37.5	40.2	49.8	59.1	100.0	100.0	100.0
4	8.4	12.0	12.0	12.0				50.0	53.6	66.4	78.8	100.0	100.0	100.0
5	10.5	15.0	15.0	15.0				62.5	67.0	83.0	98.5	100.0	100.0	100.0
6	12.6	18.0	18.0	18.0				75.0	80.4	99.6	100.0	100.0	100.0	100.0
7	14.7	21.0	21.0	21.0				87.5	93.8	100.0	100.0	100.0	100.0	100.0
8	16.8	24.0	24.0	24.0				100.0	100.0					
9	18.9	27.0	27.0	27.0				100.0	100.0					
10	21.0	30.0	30.0	30.0				100.0	100.0					
11	23.1	33.0	33.0	33.0				100.0	100.0					
12	25.2	36.0	36.0	36.0				100.0	100.0					
13	27.3	39.0	39.0	39.0				100.0	100.0					
14	29.4	42.0	42.0	42.0				100.0	100.0					
15	31.5	45.0	45.0	45.0				100.0	100.0					

+2633% dynamic cliff

+495% static cliff

Not Available

Note: Type 1 and 2 were predecessors of STS and Non-STS, respectively

Label-Based Capital Cliffs

Regulatory labels create capital cliffs by applying disproportionate capital charges to similar risk profiles, distorting market incentives.

Static vs Dynamic Cliffs

Static cliffs arise from label assessments at origination, while dynamic cliffs result from **ongoing** assessments that can amplify stress.

RISK CONTROL

4. Label (STS and Resilience) Cliffs (2/3)

Bank Capital Impact of Losing **STS** or **Resilient** Status:

			Current		Proposed							
					STS				Non - STS			
					Res.		Non-Res		Res.		Non-Res	
Asset Class	IRB Pool RW	Attachment Point	STS	Non-STS	Orig	Inv	Orig	Inv	Orig	Inv	Orig	Inv
Corporate	76.20	7.24	13.21	26.70	7.62	7.62	7.62	13.21	15.81	N/A	15.81	26.70
SME	84.91	9.05	10.00	19.00	8.49	8.49	8.49	9.24	12.74	N/A	12.74	19.00
Residential mortgage	27.38	2.89	10.00	23.96	5.00	5.00	7.00	7.42	14.85	N/A	14.85	20.46
Retail - other	65.65	7.30	17.85	51.66	6.56	6.56	7.00	16.22	30.86	N/A	30.86	47.94
Corporate	Percentage vs STS RWs			102.13	Percentage vs STS RWs				107.50	N/A	107.50	102.13
SME				89.96					50.00	N/A	50.00	105.51
Residential mortgage				139.63					196.99	N/A	112.14	175.70
Retail - other				189.46					370.08	N/A	340.86	195.48

Impact of New Resilience Labels

New labels on resilient securitisation and senior tranche holders may exacerbate cliff effects if assessed continuously.

Policy Recommendations

Confine label tests to origination or introduce smoothing mechanisms to avoid abrupt capital requirement jumps during downturns.

RISK CONTROL

4. Label (STS and Resilience) Cliffs (3/3)

- Are static cliffs justified on data?

Annualised Volatility of European RMBS Deals

	AAA Senior		AAA - All		AA- All	
	STS	Non-STS	STS	Non-STS	STS	Non-STS
Average Volatility	0.57	0.53	0.56	0.52	1.67	1.06
Index Volatility	0.27	0.17	0.25	0.17	0.98	0.43
Risk Weight	10.28	6.67	9.57	6.39	37.86	16.47
Counts	72	49	82	51	48	66

- Interpreting the evidence gap

  These results do not imply that STS transactions are riskier in a fundamental credit sense, nor that they should attract higher capital charges. Rather, they highlight that the current magnitude of label-based capital differentials is not well grounded in observable risk measures.

Market Risk Comparison
STS and Non-STS securities show similar market risk levels based on price volatility analysis.

Capital Treatment Discrepancies
Large capital differences between STS and Non-STS labels are not justified by observed risk data.

Regulatory Implications
Label-based capital adjustments require careful calibration to avoid market inefficiencies and distortions.

Need for Empirical Monitoring
Empirical analysis is essential to ensure capital differentials reflect actual risk differences.

RISK CONTROL

5. Unfunded risk transfer cliffs (1/2)

- **CRR2 (to end-2024):** Article 249(3) required CQS 2 at origination for providers of unfunded credit protection; insurers were captured via Article 201(1)(g) "other corporate entities."
- **2018-2024 market outcome:** European uncollateralised/unfunded Non-STS SRT market grew with insurers that were strongly rated at closing/origination, supporting broad transaction execution.
- **Built-in "cliff" under CRR2:** Article 249(3) also imposed an **ongoing** requirement to remain at least CQS 3, implying sharp capital increases (loss of the entire capital relief) for banks if an insurer was downgraded. A downgrade-trigger/collateral logic may be arguable for non-regulated corporates (limited prudential oversight) but does not fit regulated insurers in the same way.
- **CRR3 change (Jan-2025):** The revised CRR removed the **ongoing** test and the associated capital cliff, eliminating that instability for SRT structures.

Capital Cliffs from Rating Falls

Under CRR2, insurer downgrades caused sudden loss of credit protection recognition, triggering large capital increases.

CRR3 Regulatory Correction

CRR3 reclassified insurers as regulated entities, eliminating **ongoing** rating cliffs for unfunded credit protection.

Financial Stability Benefits

Removing rating cliffs reduced volatility in bank capital ratios and improved confidence in the regulatory framework.

RISK CONTROL

5. Unfunded risk transfer cliffs (2/2)

- **May-2025:** ESRB published a report arguing that permitting insurers to provide uncollateralised credit protection to banks via SRT deals could generate systemic risk because of a rating cliff associated with possible insurer rating downgrades.
- **Oct-2025**: An outdated EBA interactive single rulebook display contributed to ESRB/ECB positions treating the CRR2 cliff as if still applicable (by displaying the old Article 201(1)(g)). The industry alerted the ECB to the issue of the un-updated website.
- **Nov-2025**: The following month ECB issued its own opinion, without acknowledging the problem with the ESRB's position, and arguing that the CRR3 change in Article 201(1) should be reversed, i.e., **that a capital cliff be introduced** (whereupon it might be argued that ESRB's expressed concern was correct).
- **Dec-2025 reversal pressure:** the Council's Dec-2025 draft moved to reintroduce the cliff by extending Article 249(3) to insurers (via Article 201(1)(fa)), without removing the **ongoing** tests.

Policy Lessons on Eligibility Tests

Tests should ensure robustness at origination, avoiding continuous triggers that destabilize the system.

Correct Amendment for Financial Stability (EP CRR #185)

If Article 249(3) is to be reintroduced, it should be amended to keep the robustness aspects (CQS 2 requirement at origination only) and the requirement generating potential financial instability (~~CQS 3 requirement on an ongoing basis~~) should be stroked through.

RISK CONTROL

6. Opening STS Synthetic Securitisation to Insurers Without New Cliffs

- Today, insurers can only provide unfunded credit protection (UFCP) to EU banks for Non-STS.
- The new proposed SECR 26e(8)(aa) would open the STS market subject to four safeguards:
  i. Sophistication (capital model)
  ii. Robustness (credit rating)
  iii. Diversity (multiline insurers)
  iv. Size of insurer (or parent)
- Best practices applied elsewhere, '**Origination only tests**' for 'Resilient position' in the CEU/EP texts should also be applied here.
- **Ongoing** basis tests will create a new type of dynamic cliff in the regulation, especially "size cliff".

Expanding Insurer Participation
Proposed amendments allow insurers as eligible providers of unfunded credit protection, broadening investor base and risk transfer capacity.

Risks of Ongoing Safeguard Assessments
Ongoing safeguards risk causing abrupt capital cliffs and volatility for banks relying on insurer protection.

Origination-Only Safeguard Testing
Confines safeguard assessments to origination to ensure stability and avoid binary **ongoing** tests that could destabilise risk transfer.

Benefits of Proposed Approach
Supports market expansion, preserves financial stability, reduces complexity, and signals robustness of the regulatory framework.

RISK CONTROL

7. Funded, collateral and liquidity cliffs

- **Cliff effects** are not confined to capital requirements; they also arise in **liquidity regulation and collateral treatment**.
- For funded credit protection (FCP), SECR Article 26e(10) imposes collateral quality requirements that can generate both origination-time and **ongoing** liquidity cliffs. Banks may retain cash collateral only if they meet relatively stringent rating thresholds, otherwise collateral must be held with third-party institutions.
- **The Italian experience** illustrates how such rules can interact with sovereign rating constraints to create systemic challenges.
- **More concerning are the ongoing aspects of the rules**, which can force collateral transfers following downgrades, potentially draining liquidity from banks during periods of market stress. These mechanisms risk reinforcing the bank-sovereign nexus.

Collateral Quality and Liquidity Cliffs
Collateral rules impose stringent quality requirements, causing liquidity cliffs at origination and **ongoing** stages in synthetic securitisations.

Sovereign Rating Constraints
Sovereign rating ceilings limit bank collateral eligibility, creating systemic challenges and liquidity risks during downgrades.

Bank-Sovereign Nexus Risk
Downgrades can weaken banks and trigger collateral relocation, intensifying funding pressures and market stress.

Policy Recommendations
Liquidity rules should include transition periods and safeguards, aligning with economic reality to support market resilience.

RISK CONTROL

8. Conclusion

Design Principles and Policy Recommendations

- Cliffs matter because they distort incentives in normal times and amplify stress in downturns.
- The analysis of capital, label, and liquidity cliffs in EU securitisation regulations leads to a set of clear design principles for policymakers.
    1. Regulation should recognise that risk is continuous
    2. When thresholds are unavoidable, their consequences should be proportionate
    3. Ongoing eligibility tests deserve particular scrutiny.
    4. Reforms should be evaluated holistically.
- By embedding anti-cliff principles into the design of capital and liquidity rules, policymakers can support a securitisation market that is both resilient and capable of contributing meaningfully to Europe's long-term investment needs.

Smooth Risk-Based Regulation
Regulations should reflect continuous risk with smoothly varying capital requirements to avoid abrupt changes.

Graduated Thresholds
When thresholds are necessary, their impact should be proportionate with graduated steps rather than sharp jumps.

Stability in Eligibility Tests
Ongoing eligibility tests should avoid abrupt flips in regulatory status to reduce instability during stress periods.

Holistic Reform Evaluation
Capital, liquidity, and accounting rules must be evaluated together to prevent cliff effects migrating between frameworks.

RISK CONTROL

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FRONTIER MODELLING BEST PRACTICES: LEVERAGING EDW DATA TO BOOST PERFORMANCE IN FINANCIAL RISK MODELS

TOMMASO GUERRINI (CARDO AI)

CARDO AI

EUROPEAN DATAWAREHOUSE

Leveraging EDW Data to Boost Performance in Financial Risk Models

European DataWarehouse's 2026 Irish Securitisation Event - Dublin

Speaker: Tommaso Guerrini

What’s a default model

A model that estimates the probability a loan defaults (typically 90+ days past due) over a chosen horizon (e.g. 12 months). It uses loan, borrower data and other data sources (e.g. macroeconomic data).

loan_id	issue_date	current_balance	interest_rate_%	days_past_due	nace_code	region	default_flag	PD
IE-00041	2018-03-12	184,500	3.85	0	C-21	Dublin	0	0.012
IE-00042	2017-11-04	62,000	4.4	91	G-47	Limerick	1	0.873
IE-00043	2019-06-21	310,000	3.1	0	F-41	Cork	0	0.021
IE-00044	2020-09-15	48,750	5.2	32	I-56	Galway	0	0.084
IE-00045	2019-02-08	127,800	4.05	0	J-62	Dublin	0	0.018
IE-00046	2021-04-22	95,200	4.75	0	G-46	Kildare	0	0.024

Why PD models matter:

- Provisions - IFRS9 ECL
- Capital - Basel IRB
- Pricing - risk-based
- Early warning - portfolio monitoring

Different Portfolios, same drivers

Consider the following scenario:

Portfolio 1

SME
Northern Italy / Lombardy
Manufacturing-heavy
2018-2022 vintage
€250k average ticket
3% default rate

Portfolio 2

SME
Southern Italy / Sicily
Hospitality-heavy
2020-2024 vintage
€70k average ticket
7% default rate

A model trained just on one, will underperform on the other, learning segment-specific patterns.

Show the model many different segments, and only the patterns that hold across all of them survive training. Segment-specific quirks cancel out. What remains are the actual drivers of default: cash flow stress, leverage, payment behaviour, and macro sensitivity.

You need breadth

An ML model only learns from patterns it has seen at training. The broader the range, the more it can generalise to a portfolio different from any single source. A default model needs:

- **Multiple economic cycles**: sovereign stress (2011), inflation/rates shock (2022), and everything in between. A model trained only on benign years won't recognise a stress regime when it arrives.
- **Multiple underwriting strategies/policies**: different banks lend to different debtors with different rules. A model trained on one bank's data might learn those rules, not credit risk itself.
- **Multiple geographies and sectors**: risk moves differently across regions and NACE codes.
- **Enough labelled defaults**: defaults are rare events, and robust modelling needs many of them.

Even the largest banks see only their own slice: one underwriting policy, one customer mix, one geography. The **obvious option is to pool data across banks**. **Breadth at training is what lets a model work on a portfolio it has never seen**, even when that portfolio is structured differently from anything in the training data.

But schemas don’t match

Consider the following scenario: an ML model is trained on bank A’s portfolio, consisting of some loan and borrower information.

bank A

Loan Tape

L001, €5.000, 4.7%
L002, €6.500, 6.7%

Borrower info

L001, Hospitality, Dublin, BBB
L002, Construction, Cork, BB

But schemas don’t match

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Borrower info

L001, Hospitality, Dublin, BBB
L002, Construction, Cork, BB

bank B

Loan Tape

L001, €4.000, 5.7%
L002, €5.200, 7.2%

Borrower info

L001, Tech, Galway, BBB+
L002, Logistics, Dublin, BB

Payments/Transactions

L001, -€700, 2026-03-28
L001, -€320, 2026-04-02

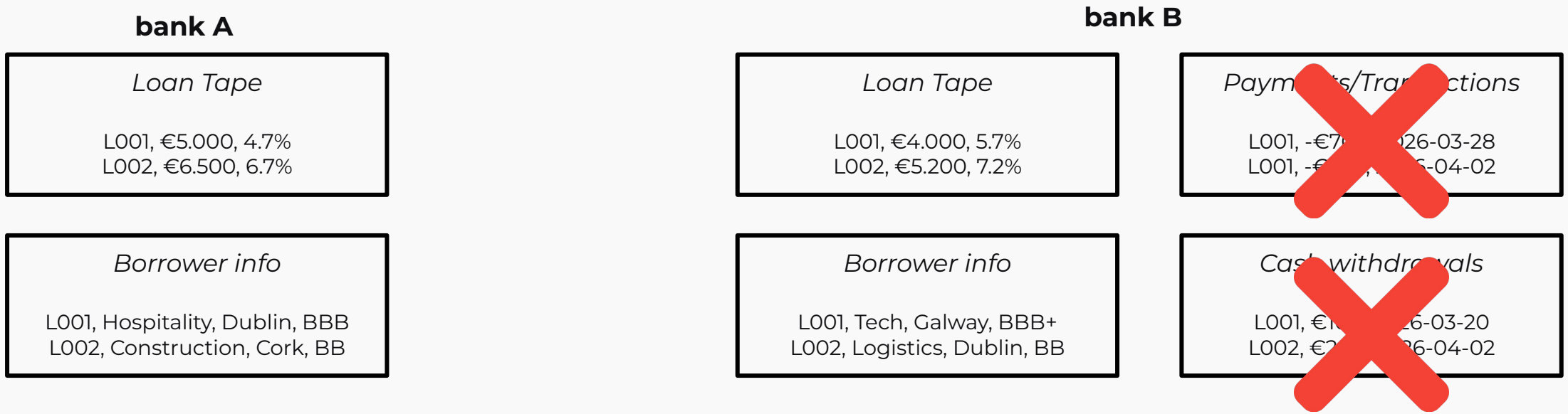
Cash withdrawals

L001, €100, 2026-03-20
L002, €200, 2026-04-02

After that the model needs to score bank B’s portfolio, which has additional information, like Transactions and Cash withdrawals.

But schemas don’t match

99% of SOTA ML models are **tied to the schema they were trained on**. Change the columns, types or definitions and the model can’t be deployed, **you retrain from scratch**.



an ML model trained on bank A **can’t use the additional information** from bank B. It needs retraining on the new data. Typically these models also need hundreds of thousands of loans to be effective.

Different column names, types, granularity, columns don’t overlap. **There is a need for standardization/pooling**.

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Pools exist but not for this

1. Some pooling happens, inside closed bank-only consortia. e.g. Global Credit Data (GCD)

2. Usually banks don't open their tapes more widely, for competitive reasons: A vendor that learns from Bank A's tape and then serves Bank B is exactly what Bank A's underwriting team won't sign off on

3. What we need to deploy a vendor-built default model on a bank's portfolio:
   a. loan-level data
   b. Retail / SME / mortgage, not just large corporate
   c. multi-originator and standardized
   d. Sourced from securitisation disclosure data, i.e. already pooled in EDW by EU regulation, across many originators

The data we need is already pooled in EDW.

EDW: the pool built for this problem

- **Loan-level by regulation**: ESMA-mandated reporting templates for securitised portfolios mean every loan, every period, lands in a comparable, standardised schema

- **Broad asset-class coverage**: RMBS, ABS-SME, ABS-auto, leasing, NPL, consumer. Where existing consortia focus on commercial and low-default, EDW spans the retail and SME breadth

- **decades of data across cycles**. Sovereign stress (2011), inflation/rates shock (2022), and everything between, multiple originators, multiple geographies, in one place.

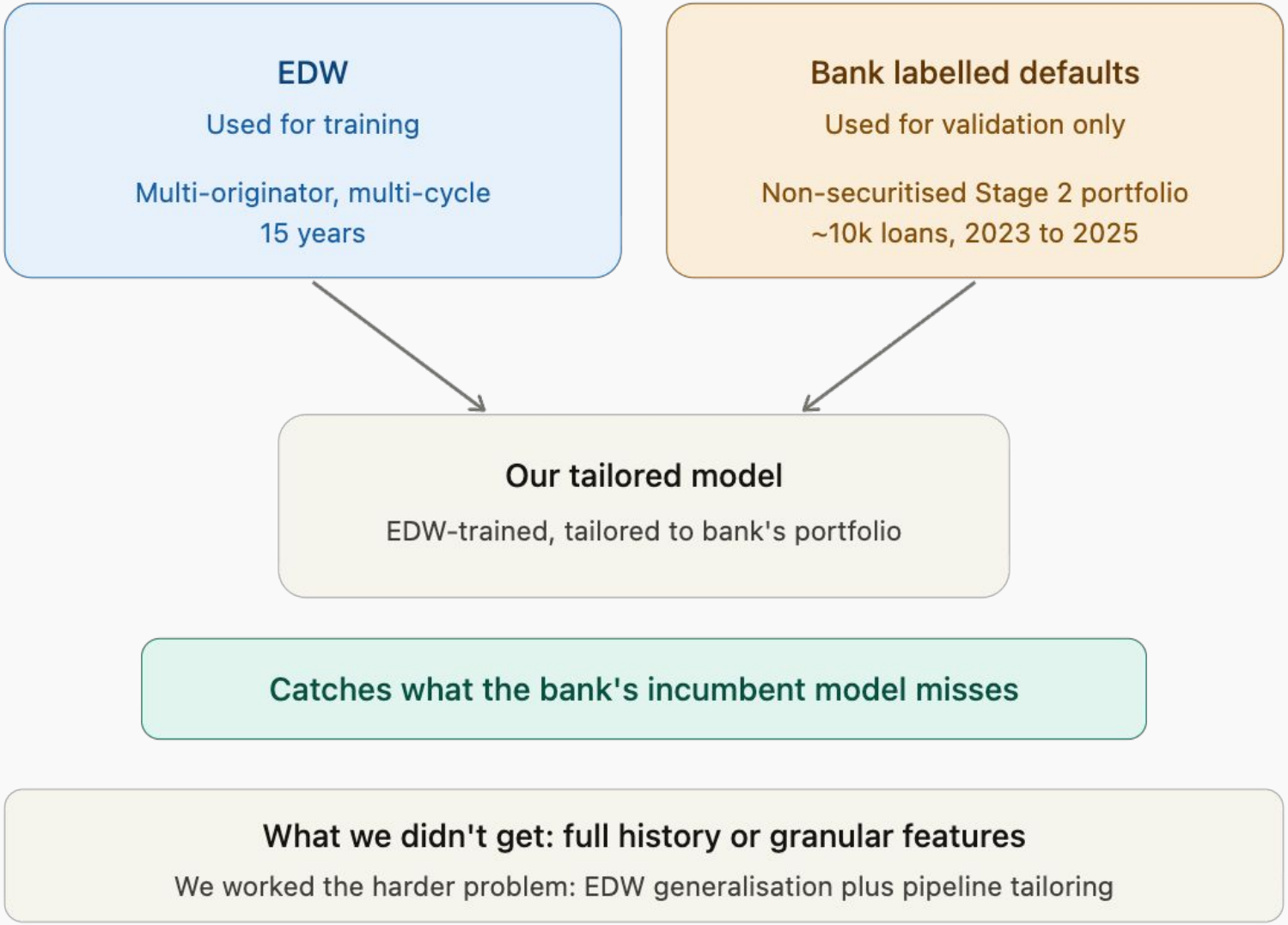
For our use case:

- 2011-2026 Italian SME loans
- all regions and sectors
- ~1M loans

EUROPEAN DATAWAREHOUSE

From EDW to your portfolio: a concrete use case

Pilot: anonymised mid-size regional bank, retail SME book



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From EDW to your portfolio: a concrete use case

Goal of the Project: A multi-horizon stage 2 → 3 transition detection platform that is able to produce targeted models on new portfolios, non-securitized, complementing what banks have internally with alternative data.

Issues	Cardo AI Solution
Diverging table schemas	Schema mapping aligns the bank's tape to the EDW schema at inference
Non securitized positions	Coverage check drops/simplifies features unreliable outside the securitized perimeter
Non standard IFRS9 Stage 2 definitions	Validation on the bank's labelled subset calibrates the model to their Stage 2 definition before go-live
Lack of alternative risk drivers	Feature engineering with macro, regional, sector-level, and energy/fuel-consumption signals
Asset class/product type diverging from the original model	Adversarial population-fit check reweights training toward the bank's sector mix, ticket size, and geography

What about useful information (e.g. transaction-level) the bank has but EDW/training data doesn't? Current models are not able to exploit them without a full dataset to retrain on, but ***Tabular Foundation Models change this.***

The takeaway and results

Your portfolio is what we predict on, not what we train on:

EDW provides the breadth, alternative data + our ML pipeline optimize on your portfolio. We don't require your full historical data to deploy our model. (add validation)

On the bank's portfolio, our ML model:

- ***detects 18% more stage 2 -> 3 transitions compared to the bank's baseline***
- ***anticipates the transitions by up to 6 months earlier than the bank's baseline***

Validated out-of-sample on 2023–2025, on the subset of loans with sufficient observation history.
Early warnings give credit teams months to act before loans default.

Two shifts reshaping credit modelling

Our industry has been building default models the same way for nearly a decade: lots of data, gradient boosting, manual onboarding per bank. Two things are changing that, and at CardoAI we're tracking both with concrete experiments.

Shift 1: AI agents in the ML pipeline

Schema mapping, feature engineering, hypertuning, performance diagnostics: automated and orchestrated, **speeding up the onboarding time per bank**.

Shift 2: Tabular foundation models

A new model class matching or beating gradient boosting with a fraction of the labelled data.
Less data is needed to deploy a model, unlocking the bank's granular features beyond what EDW reports.

Less time to onboard. Less data needed. More accurate models.
Agents drive the first; TFMs drive the rest.

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Shift 1: AI agents in the ML pipeline

Every ML pipeline has some **siloed/repetitive** components:

- data ingestion
- data preprocessing and feature engineering (where the mapping bank -> EDW stands)
- model training and hypertuning (the actual “tailoring” of our model to the bank’s portfolio)
- model diagnostics and monitoring (how our model performs)

Automating these components with dedicated agents is now a measurable research direction. **OpenAI**'s **MLE-Bench** (2024) evaluates AI agents on 75 Kaggle competitions covering exactly this work: dataset preparation, model training, experimentation

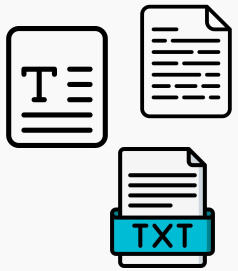
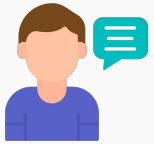
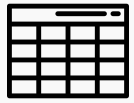
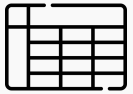
Where do agents come in handy?

- schema changes between each portfolio and needs custom handling
- the agent might suggest/retrieve new features based on the portfolio uploaded by the bank
- an agent that might reply to user questions about model performance and explainability

We are building a knowledge base (through documentation and skills in .claude) that will power dedicated agents, ***speeding up each new bank onboarding.***

Shift 2: Tabular foundation models

How they function: a parallel with LLMs

	PRE-TRAINING	INFERENCE	GENERALIZATION and FINE-TUNING
LLM	pre-trained on trillions of words 	 Gets a prompt. Better context (relevant docs, examples, background) -> better answer. Model weights don't change.	 Works on questions never seen at training. Can be fine-tuned on domain corpora (legal, medical, code) → specialist LLM for that domain (e.g. BloomberGPT for finance, Harvey for legal).
TFM	pre-trained on hundreds of millions (TabPFN) of synthetic generated tables 	 Gets a small labelled set. Better context (similarly distributed loans — same region, sector, size, mixing defaulted and performing) -> better prediction. Model weights don't change.	 Works on portfolios never seen at training. Can be fine-tuned on EDW (15 years of loan-level, multi-originator data) → specialist TFM for credit risk.

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Shift 2: Tabular foundation models

What changes with in-context (prompt) learning?

Let’s go back to the previous example.

bank A

Loan Tape

L001, €5.000, 4.7%
L002, €6.500, 6.7%

Borrower info

L001, Hospitality, Dublin, BBB
L002, Construction, Cork, BB

bank B

Loan Tape

L001, €4.000, 5.7%
L002, €5.200, 7.2%

Payments/Transactions

L001, -€ 03-28
L001, -€ 04-02

Borrower info

L001, Tech, Galway, BBB+
L002, Logistics, Dublin, BB

Cash withdrawals

L001, € 03-20
L002, € 04-02

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Shift 2: Tabular foundation models

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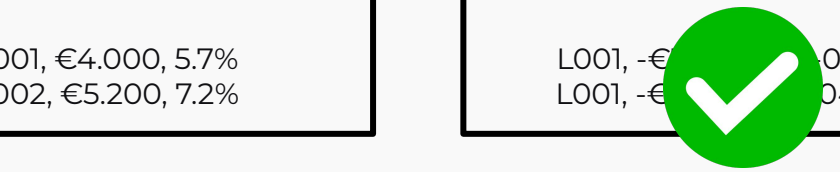

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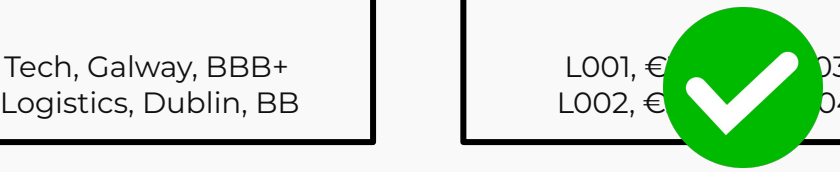
Cash withdrawals

L001, € 03-20
L002, € 04-02



Earlier we said: what wasn't there at training can't enter at inference. **With in-context learning**, that no longer holds. Bank B's **payments and cash withdrawals enter the model at inference, as context**. No retraining required.

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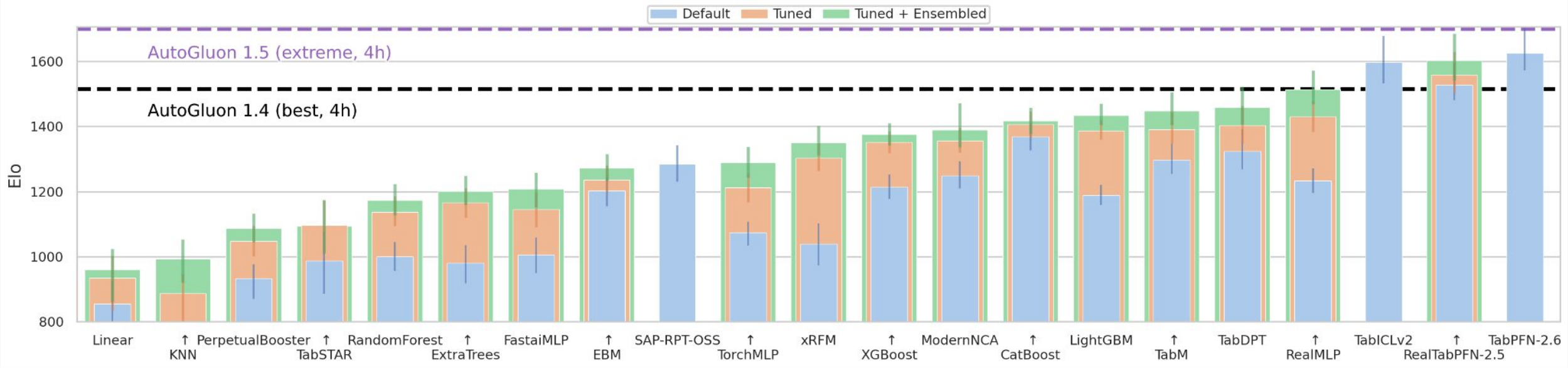
Shift 2: Tabular foundation models

How they perform: a parallel with LLMs

For nearly a decade, gradient-boosted trees have been the SOTA for tabular data. In the last 12 months, **tabular foundation models** (TabPFN, TabICL, Kumo RFM-2, etc) **have been consistently outperforming GBMs** on standard benchmarks*, especially on small datasets (500-10k samples).



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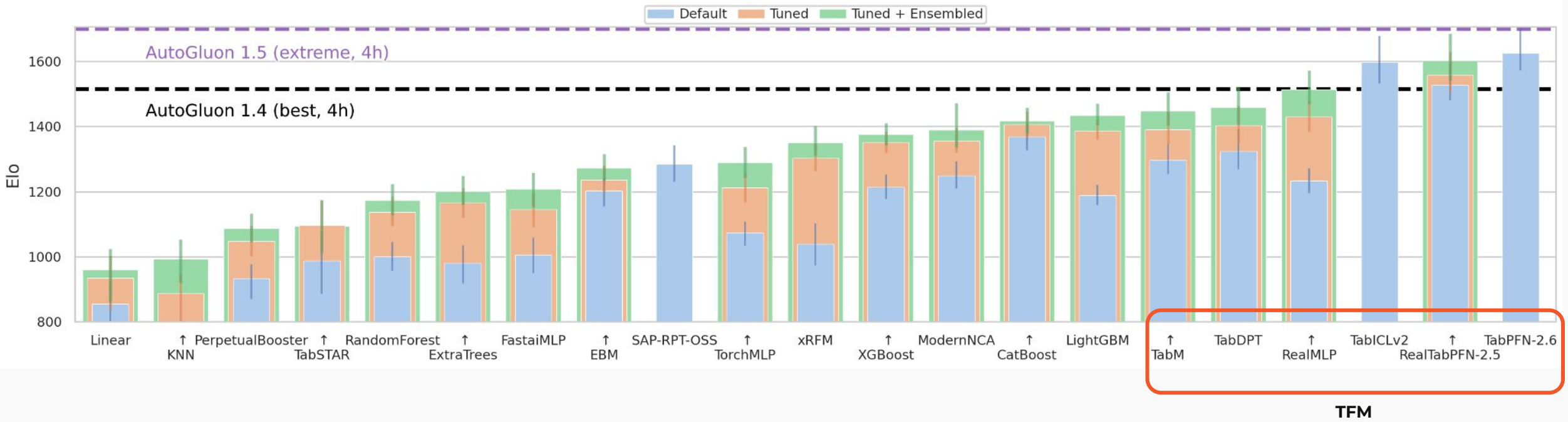

*Source: TabArena — Elo leaderboard for tabular ML
Check Backup slides for a deep dive on performance

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Shift 2: Tabular foundation models

Why this matters for credit risk?

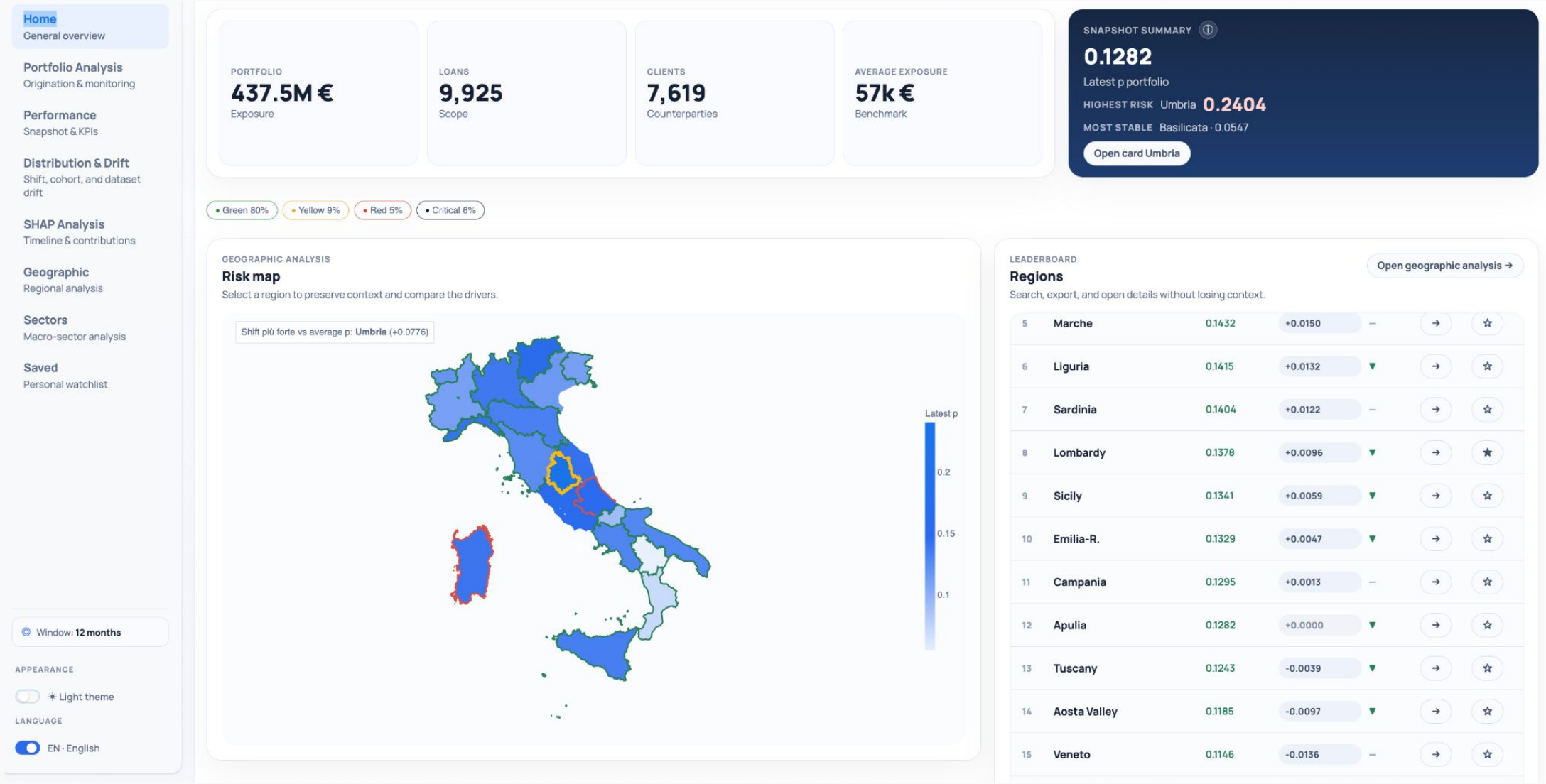
- **Onboarding shifts from retraining to context selection:** currently, whenever something changes in the schema or in the distribution, GBM models need to be retrained. With TFMs the model stays the same, anything new (schema or distribution) is put in context. From 100k loans to 2k loans.

- **Richer bank data, no schema constraint:** Behavioral signals, transaction patterns, payment-withdrawal sequences are all unlocked thanks to in-context learning from TFMs.

- **EDW becomes the fine-tuning corpus:** Same way Harvey fine-tuned GPT-4 on legal corpora, a TFM fine-tuned on EDW (15 years, loan-level, multi-originator, multi-asset) becomes a credit specialist.

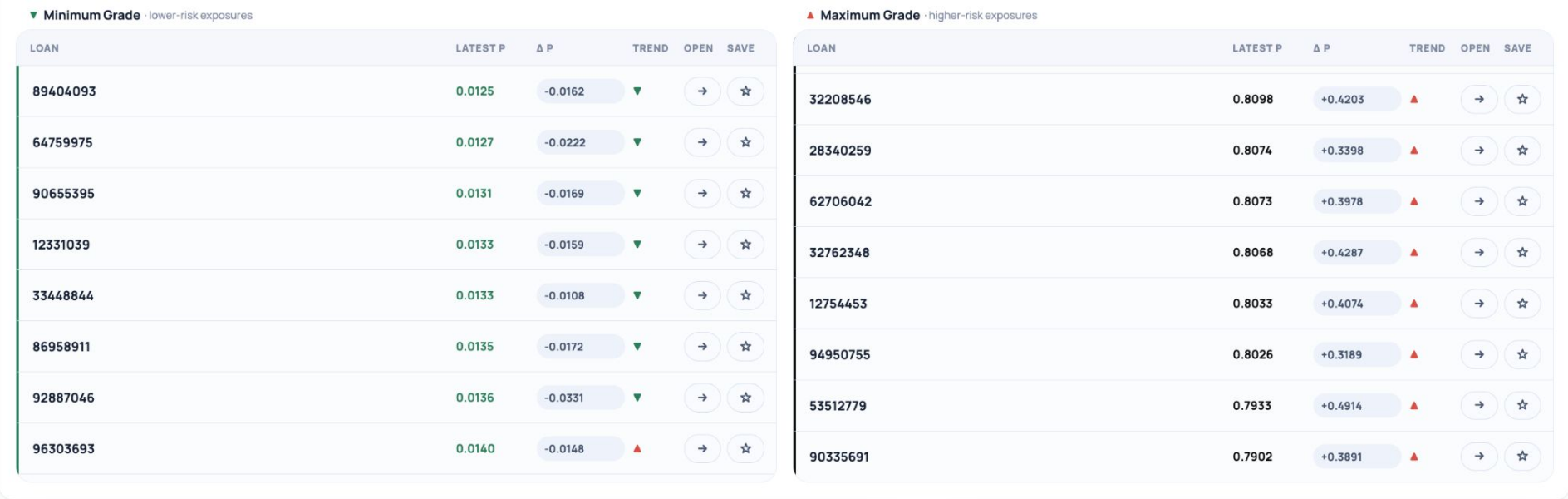
Internal benchmarks on the anonymised partner's portfolio (on the bank's labelled subset, with in-context examples) show **TFMs outperforming our GBM pipeline**. Still in development, not production-deployed.

Portfolio Overview: Complete control of dynamic defaults



CARDO AI

Portfolio Overview: Complete control of dynamic defaults



QUICK READ

Key signals

Risk distribution and main movers.

Snapshot summary

The Latest p distribution remains concentrated in a few regions. The spread between the riskiest and most stable area is 0.1857. The strongest shift versus p medio is Umbria (+0.0776).

HIGH PRESSURE		MOST STABLE AREAS	
Umbria	0.2404	Basilicata	0.0547
Lazio	0.1600	Calabria	0.0703
Trentino-South Tyrol	0.1545	Molise	0.0907

WATCHLIST

Watchlist focus

Latest saved items, ready for drill-down.

L 10333998-E5-0B10E…
0.3005 +0.0000

L 12801210-H2-0B10H…
0.5688 +0.0000

R Lombardy
0.1378 +0.0000

Go to watchlist →

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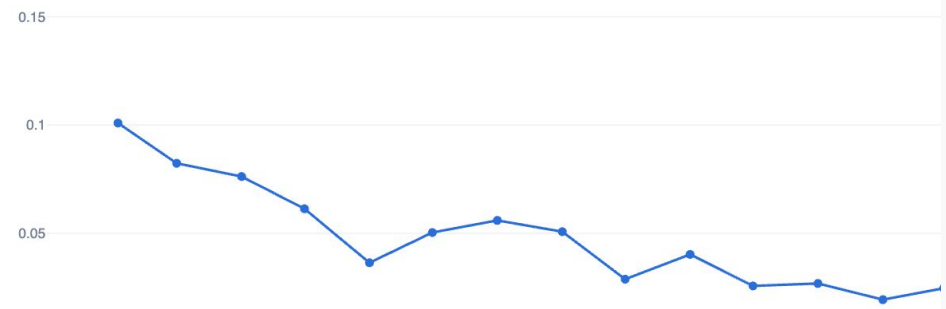
Portfolio Overview: Complete control of dynamic defaults

ID	CLIENT NAME	CURRENT P	REGION
[redacted]	[redacted]	0.0135	Piemonte

P EVOLUTION OVER TIME



The readout remains mostly bank-based, with alternative signals in a supporting role.

OVERVIEW

- Current PD is 0.0135, reflecting a decrease from the previous PD of 0.0182, maintaining a position below the threshold of 0.3157.
- The current risk profile is driven by bank factors, with a significant contribution from protective drivers such as Capitale corrente / capitale originario at SHAP -0.7916 and Durata finanziamento at SHAP -0.2332, while alternative signals account for 16.6% of the total signal, contributing negatively at -0.3561, primarily driven by value_nace_benford_correlation at SHAP -0.0839, which offsets the bank-driver story.
- Recent changes include a notable decrease in PD attributed to protective drivers, particularly a reduction in the impact of Ricavi and Presenza garanzia reale, with approximate PD changes of +0.0008 and +0.0006 respectively; monitoring of these drivers is essential as they exhibit volatility.

SUPPORTING EVIDENCE

- PD decreased by 0.0046 to 0.0135, currently below the attention threshold.
- Top risk drivers: Ricavi (0.052).
- Most protective factors: Capitale corrente / capitale originario (-0.792), Durata finanziamento (-0.233).
- Main worsening contributors vs previous: Ricavi (Δ0.001), Presenza garanzia reale (Δ0.001).
- The loan sits at the 0th percentile of the Region: PIE cohort (2695 loans).
- Stable drivers over 11 snapshots: Tasso d'interesse, Numero di giorni di arretrato, Importo finanziamento originario.

CARDO AI

Portfolio Overview: Complete control of dynamic defaults

EXPLANATION QUALITY

Driver stability

Which drivers are structural vs episodic over the available history.

DRIVER	AVG ISHAPI	STD DEV	SIGN FLIPS	TOP-5 PERSISTENCE	TREND	STABILITY
Capitale corrente / capitale originario	0.4022	0.2135	0	91%		Variable
Tasso d'interesse	0.2130	0.0720	0	91%		Stable
Numero di giorni di arretrato	0.2066	0.0248	0	100%		Stable
Importo finanziamento originario	0.1802	0.0541	0	73%		Stable
Durata finanziamento	0.1577	0.0677	0	64%		Stable
EBITDA	0.1202	0.0474	0	36%		Stable
Value Nace Benford Correlation ALT	0.1129	0.0306	0	18%		Stable
Limite di credito	0.0858	0.0752	2	27%		Variable
Debito totale corrente utilizzato	0.0458	0.0337	2	0%		Variable
Variazione giorni di arretrato vs mese precedente	0.0410	0.0097	0	0%		Stable

Based on 11 historical snapshots for this loan.

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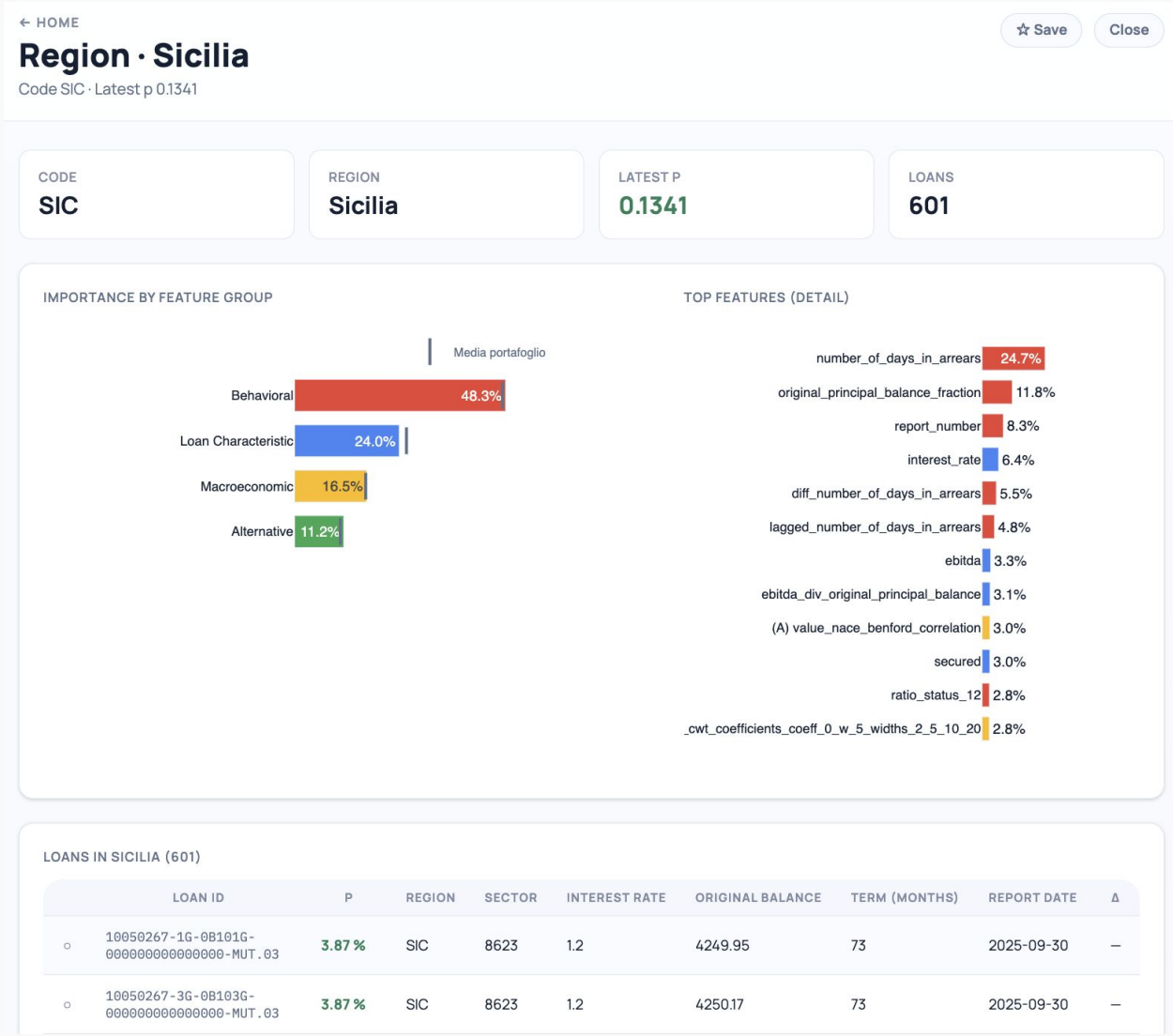
Portfolio Overview: Complete control of dynamic defaults



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Conclusions

Three takeaways

1. Deployment in weeks, not months.

EDW gives us the breadth. Our pipeline gives us the speed, encoded today as reusable skills, tomorrow as agents. Your portfolio is what we predict on, not what we train on.

2. Less data, more signal.

A few thousand labelled loans from your portfolio is enough to tailor. As we move to TFMs, even your richest features (transaction patterns, behavioral signals) flow in as context without retraining.

3. CardoAI sits at the intersection of two shifts.

Agents in the ML pipeline. Tabular foundation models for credit. We're implementing the first today and prototyping the second on EDW data.

THANK YOU!

BACKUP

From EDW to your portfolio: a concrete use case

EDW is securitised loans. My book isn't. Why would a model trained on EDW work on my portfolio?

Our **use case:**

- Our pilot was on **non-securitised loans**: the retail SME book of a mid-size Italian banking partner.
- they have an **internal model** which uses granular data we don't have (transaction-level, payments, withdrawals from company accounts). Their goal is to catch loans their model doesn't, leveraging **EDW generalization power and alternative data risk drivers.**
- The EDW-trained model is the starting point, not the final product. We tailor it to the bank's actual population through our pipeline (next slide).
- **Training data: EDW only.** Their labelled defaults are used to validate performance and benchmark TFM approaches, never to train the production model. Data sovereignty is intact.
- **What we'd have wanted, didn't get**: their full historical loan book and the granular features behind their internal model. So we worked the harder problem: generalisation from EDW plus alternative data, tailored through our pipeline.

From EDW to your portfolio: a concrete use case

1. **Train on EDW + alternative data + feature engineering:** Gradient-boosting model trained on EDW Italian SME loans, enriched with public macroeconomic indicators, regional and provincial economic signals, sector-level activity data, and energy/fuel consumption trends. All alternative data gets transformed in order to improve the portfolio predictability. Backtested across multiple years.

2. **Map the bank's schema to the EDW schema:** as said previously, at inference/deployment time the model has to see the same schema it was trained on.

3. **Optimize the pipeline on the bank's tape:**
   a. **Coverage check:** Features that the model relies on, but are either missing or unreliable in the bank's portfolio, are dropped or simplified
   b. **Population fit check:** Adversarial validation to detect where the bank's portfolio diverges from the EDW population (sector mix, ticket size, geography, etc.) . We want to use data that is more relevant to the bank's portfolio

4. **Validate on the bank's labelled subset before going live:** we don't train on this, we use it to validate our approach.

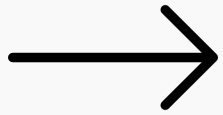
5. **Deploy for inference and monitor (ongoing)**

What about useful information (e.g. transaction-level) the bank has but EDW/training data doesn't? Current models are not able to exploit them without a full dataset to retrain on, but ***Tabular Foundation Models change this.***

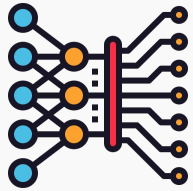
But schemas don’t match

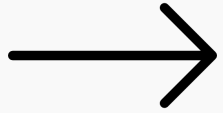
bank A

column	type
cust_id	varchar
contract_dt	date
princ_outst	numeric
princ_orig	numeric
int_rate_pct	numeric
dpd	integer
ateco	varchar
region_code	char(3)
collateral	varchar
ltv_pct	numeric
internal_rating	varchar
npe_flag	bit



ML model





bank B

field_name	data_type
borrower_key	string
start_date	datetime
outstand[illegible]nt	flo[illegible]
nominal_ra[illegible]	
arrears_bucke[illegible]	[illegible]m
nace_section	[illegible]ar(1)
nace_divisi[illegible]	[illegible]r(5)
province	str
guarantee_type	string
behavioural_score	float
loan_purpose	string
status	enum

a model trained on the left tape **can’t be used/deployed on the right one**. Different column names, types, granularity, columns don’t overlap. **There is a need for standardization/pooling**.

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But schemas don’t match

99% of SOTA ML models are **tied to the schema they were trained on**. Change the columns, types or definitions and the model can’t be deployed, **you retrain from scratch**.

bank A

column	type
cust_id	varchar
contract_dt	date
princ_outst	numeric
princ_orig	numeric
int_rate_pct	numeric
dpd	integer
ateco	varchar
region_code	char(3)
collateral	varchar
ltv_pct	numeric
internal_rating	varchar
npe_flag	bit

bank B

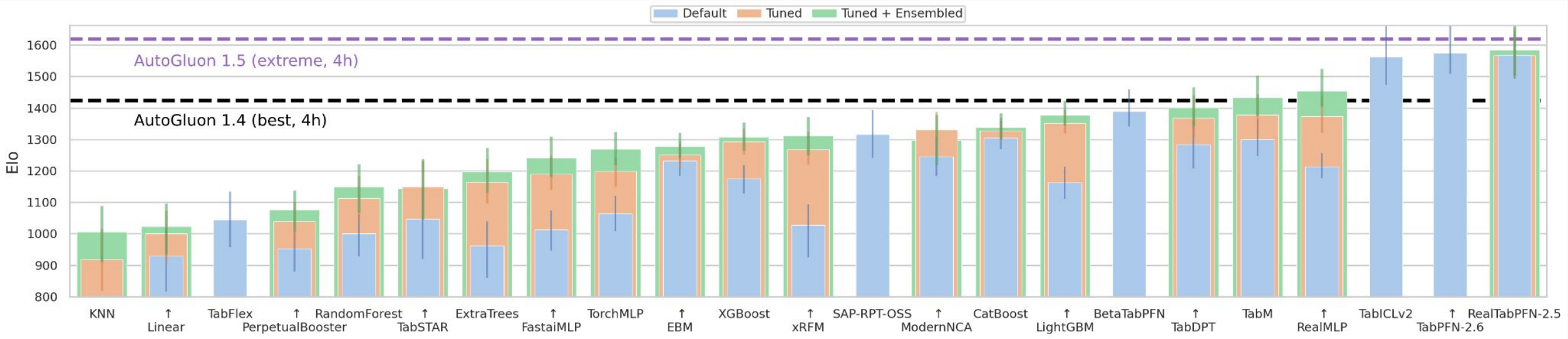
field_name	data_type
borrower_key	string
start_date	datetime
outstanding_amt	float
nominal_rate	float
arrears_bucket	enum
nace_section	char(1)
nace_division	varchar(5)
province	string
guarantee_type	string
behavioural_score	float
loan_purpose	string
status	enum

a model trained on the left tape **can’t be used/deployed on the right one**. Different column names, types, granularity, columns don’t overlap. **There is a need for standardization/pooling**.

Tabular foundation models Benchmarks

The most popular benchmark for tabular data is TabArena*, a continuously updated benchmark that tracks tfm, gradient boosting, deep learning and other models through ELO rating. One thing to notice is that the statement "*TFMs are consistently outperforming GBMs on tabular data*" is particularly true on Small datasets (500-10k samples). On Big datasets (>250k) GBMs are still SOTA, but TFMs are catching up. See the following images:

TabArena Elo Rating on Small Classification datasets (500-10k samples)



the best GB model is LIghtGBM which comes in at 8th place, almost 200 Elo points behind the best TFMs.

*Erickson et al., 2025 - arxiv.org/abs/2506.16791 · leaderboard at tabarena.ai

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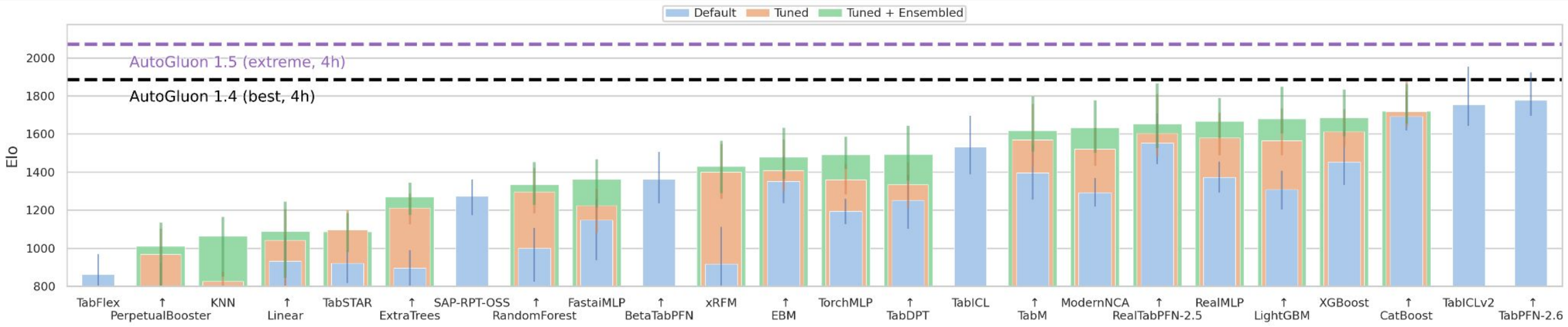
Tabular foundation models Benchmarks

The most popular benchmark for tabular data is TabArena*, a continuously updated benchmark that tracks tfm, gradient boosting, deep learning and other models through ELO rating. One thing to notice is that the statement "*TFMs are consistently outperforming GBMs on tabular data*" is particularly true on Small datasets (500-10k samples). On Big datasets (>250k) GBMs are still SOTA, but TFMs are catching up. See the following images:

TabArena Elo Rating on Medium Classification datasets (10k-250k samples)



GB models are much closer to the best performers in terms of ELO (<100), 3 out of 5 best models are GBMs.

*Erickson et al., 2025 - arxiv.org/abs/2506.16791 · leaderboard at tabarena.ai

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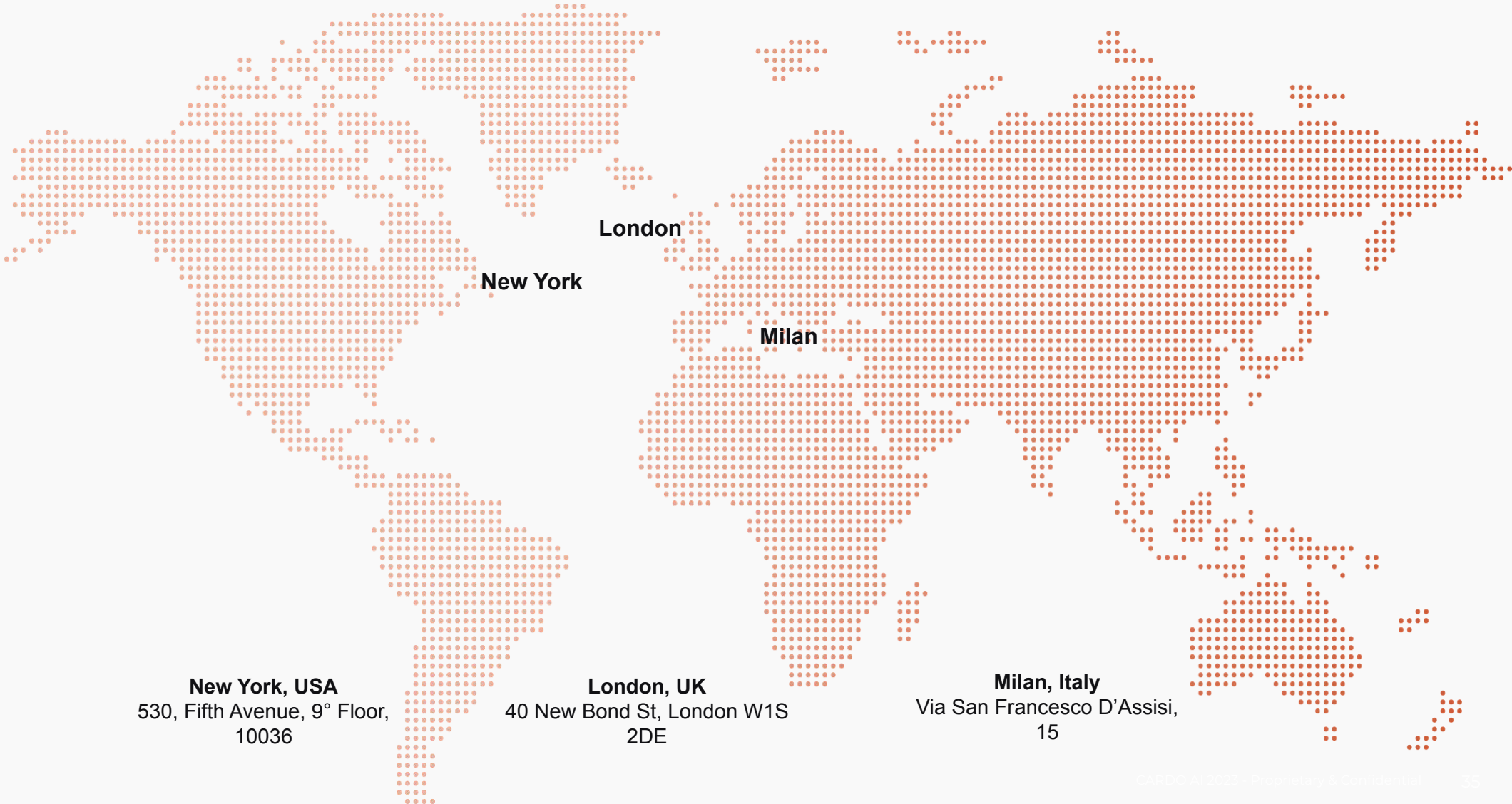

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DEALDOX®: A DATA ROOM FOR SECURITISATION

SAMUEL STANIS (EDW)

THE CHALLENGE

THE PROBLEM

Issuers were stretching EDITOR into a virtual data room.

- Built for regulatory reporting
- Never designed for collaboration
- No deal structuring tools
- No stakeholder coordination

MARKET SCAN

EDW evaluated every leading VDR provider.

- None understood securitisation
- Generic approach
- No regulatory awareness
- No deal-lifecycle management

THE GAP

Private deal volumes were growing fast.

- Issuers needed more than reporting
- Investors needed structured access
- Arrangers needed real collaboration
- No SINGLE tool met all of these needs

THE DECISION

We chose to build it ourselves.

- In the best interest of our customers
- Designed by the securitisation experts
- Built for securitisation experts
- Embedded in the EDW ecosystem

DEALDOX

OUR PRIORITIES

THE FOUR CORE PRINCIPLES BEHIND DEALDOX®

SPEED & FLEXIBILITY

Launch deals faster with pre-built templates, one-click setup, and zero naming conventions.

SECURITY

Bank-grade security with SOC2 Type 1 & 2, and ISO 27001 certifications, DORA compliance.

CONTROL

Granular permissions, NDA management, and full audit trails keep every stakeholder on the right track.

COMPLIANCE

Native ESMA, FCA, and Prospectus Regulation support. Submit directly from within the deal room.

BUILT FOR

- ISSUERS
- ARRANGERS
- INVESTORS
- LAW FIRMS
- RATING FIRMS

YOUR DEAL, YOUR DATA

DEALDOX® IS YOUR PRIVATE WORKSPACE

DEALDOX®	GENERIC DATA ROOMS
Used from structuring through to reporting	Closing-phase tool only
Securitisation specific folder templates	Generic templates
Monthly billing — pause when you want	Annual contracts of variable usage fees
Deal Tracker with phases and milestones	No lifecycle project management
Built specifically for securitisation workflows	Generic, one-size-fits-all approach

FROM STRUCTURING TO CLOSING IN ONE WORKSPACE

EVERYTHING YOUR DEAL TEAM NEEDS ON A SINGLE PLATFORM

STRUCTURE

Set up rooms with sector templates, folder structures and milestones in minutes.

COLLABORATE

Coordinate with every deal stakeholder in one place with NDA management, Q&A modules, and custom permissions.

SUBMIT & REPORT

Convert loan tapes to ESMA/FCA XML and publish public pages directly from the room.

COLLABORATION AND CONTROL

EVERY STAKEHOLDER INTERACTION MANAGED INSIDE THE DEAL ROOM

PERMISSION GROUPS

Give the right access to the right team. Bulk edit, view, edit, and download rights.

DOCUMENT SIGN-OFF

Request and track stakeholders sign-off in real time, then mark final documents once they are approved.

VERSION CONTROL

Every upload is versioned automatically, view history and roll back to see changes in real-time.

FOLDER TEMPLATES

Start from sector-specific templates like ABS public & private, covered bonds, CLOs, and many more.

LIVE CO-EDITING

Collaborate on Word, Excel, and PDFs in real time, with presence indicators.

WATERMARKING & AI

Protect sensitive drafts with dynamic watermarks on every view and download.

NEVER MISS A MILESTONE

DEAL TRACKER: A PROJECT-MANAGEMENT TOOL INSIDE EVERY DATA ROOM

TEMPLATES

Ship faster with predefined lifecycle templates that map every phase, milestone, and document.

MILESTONES

Track scheduled and actual dates, variances, notes, and link closing documents.

PHASES

Define you own phases and build around how your team works best.

LIFECYCLE	PRE-ISSUANCE	ISSUANCE	REPORTING SETUP	ONGOING REPORTING	EVENTS

BUILT FOR COMPLIANCE

MEET EU, UK, AND PROSPECTUS REGULATION REQUIREMENTS FROM ONE DATA ROOM

ESMA	**EU REPORTING, NATIVE** Generate loan-level XML files with automatic schema validation; publish to the EDW EDITOR in one click.
FCA	**UK REPORTING, SAME ROOM** One workspace for both regimes; switch between EU and UK tape production without re-entering data.
PROSPECTUS	**PUBLIC DISCLOSURE LINK** Create a no-login public website per deal, with chosen folders, logos, and custom URLs.

UPCOMING WEBINAR, MASTERCLASS SERIES, OR SCHEDULE A DEMO

28 MAY

Launch Webinar:
European DataWarehouse Introduces **DealDox®**

24 JUNE

Master Class 1:
Your First Deal Room in 10 Minutes

1 JULY

Master Class 2:
Keeping Transactions Compliant & Transparent

8 JULY

Master Class 3:
Faster Transaction Setup

15 JULY

Master Class 4:
Smooth Collaboration Throughout the Deal Lifecycle

22 JULY

Master Class 5:
Faster & Safer Access to Deals

29 JULY

Master Class 6:
What's Coming in 2027 Product Roadmap

CLICK HERE TO SCHEDULE DEMO

WHAT'S NEW? ABS STRUCTURED FINANCE

MODERATOR: MARTIN KUHN (EDW)

MICHAEL OSSWALD (SVI)

CLAIRE MCKENNA (TMF)

MARK WEEDON (ONATE)

VALERIE O'FLAHERTY (EURONEXT DUBLIN)

THANK YOU TO OUR HOST

Banc Ceannais na hÉireann
Central Bank of Ireland

Eurosystem

GLOBAL ABS STARTS HERE

Please register for our exclusive networking event in Barcelona by scanning the QR code.

DRINKS & DEALS

Monday, 8 June | 18:30 - 21:30 | Barcelona

UPCOMING WEBINARS

Scan the QR code to register for one of our upcoming virtual events

THANK YOU

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