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CECL Implementation and Model Risk In Uncertain Times

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AGENDA

- CECL before the pandemic and prior to implementation
- CECL During the pandemic - sensitivity to model and forecasting error
- Banks' adjustments to the pandemic
- Why models underperform in times of crisis.
- Strategies to mitigate CECL sensitivity to model and forecasting error.
- Designing simple models without compromising performance.
- Challenges to methodological innovations.

What is the allowance for credit losses?

- **The Allowance for Loan and Lease Losses** (ALLL) is an estimate of uncollectible amounts used to reduce the book value of loans and leases to the amount that a bank expects to collect.
- The purpose of the ALLL is to reflect estimated credit **losses** within a bank's portfolio of **loans and leases**.

Commercial bank balance sheet (2nd Q. 2019)

ASSETS		LIABILITIES AND EQUITY	
Cash	9	**Total Deposits**	576
investments	541	Short term deposits	196
Net loans	376	Longer term deposits	380
Gross Loans	381	**Total Debt**	217
Loan Loss Allowances	-5	Short term debt	114
Property, plants, equipment	6	Long term debt	103
Other assets	69	**Other Liabilities**	106
		Equity	100
TOTAL ASSETS	1000	**TOTAL**	1000

ALLL is a **contra-asset account** that reduces the **loan** portfolio amount reported on the balance sheet.

https://www.federalreserve.gov/supervisionreg/topics/alll.htm

What is CECL?

In June 16 2016 FASB issued the “Accounting Standards Update No. 2016-13” an important component this update was the Current Expected Credit Loss (CECL), a new framework for computing allowances for credit loss. CECL requires

Immediately record all expected credit losses for financial assets held at the reporting date based on historical experience, current conditions, and reasonable and supportable forecasts

Under CECL, the total amount of net charge-offs on financial assets does not change, but rather the timing of credit loss provision expenses changes.

CECL also requires enhanced disclosures.

CECL applies to Every organization required to issue financial statements in compliance with U.S. GAAP. Following US GAAP is required by the Federal Deposit Insurance Act, which says that all insured depository institutions are required to be uniform and consistent with GAAP. FDI Act – SEC 37(a)(2)(A). Banks are likely to experience the largest implementation burden.

CECL replaces,

- The “incurred loss” accounting methodology. Under this methodology, the allowance is a valuation reserve established and maintained to cover losses that are probable and estimable as of the reserve calculation date.

Objectives of CECL include,

- Better aligning the financial reporting for credit losses with the informational needs of financial statement users.

- Earlier recognition of credit losses.

These objectives necessitate “reasonable” estimates of current expected credit loss.

Themes across CECL studies prior to 2020 implementation & Covid-19.

- **CECL will be pro-cyclical**, the degree of pro-cyclicality will be conditional on the level of forecasting accuracy in anticipation of a downturn.

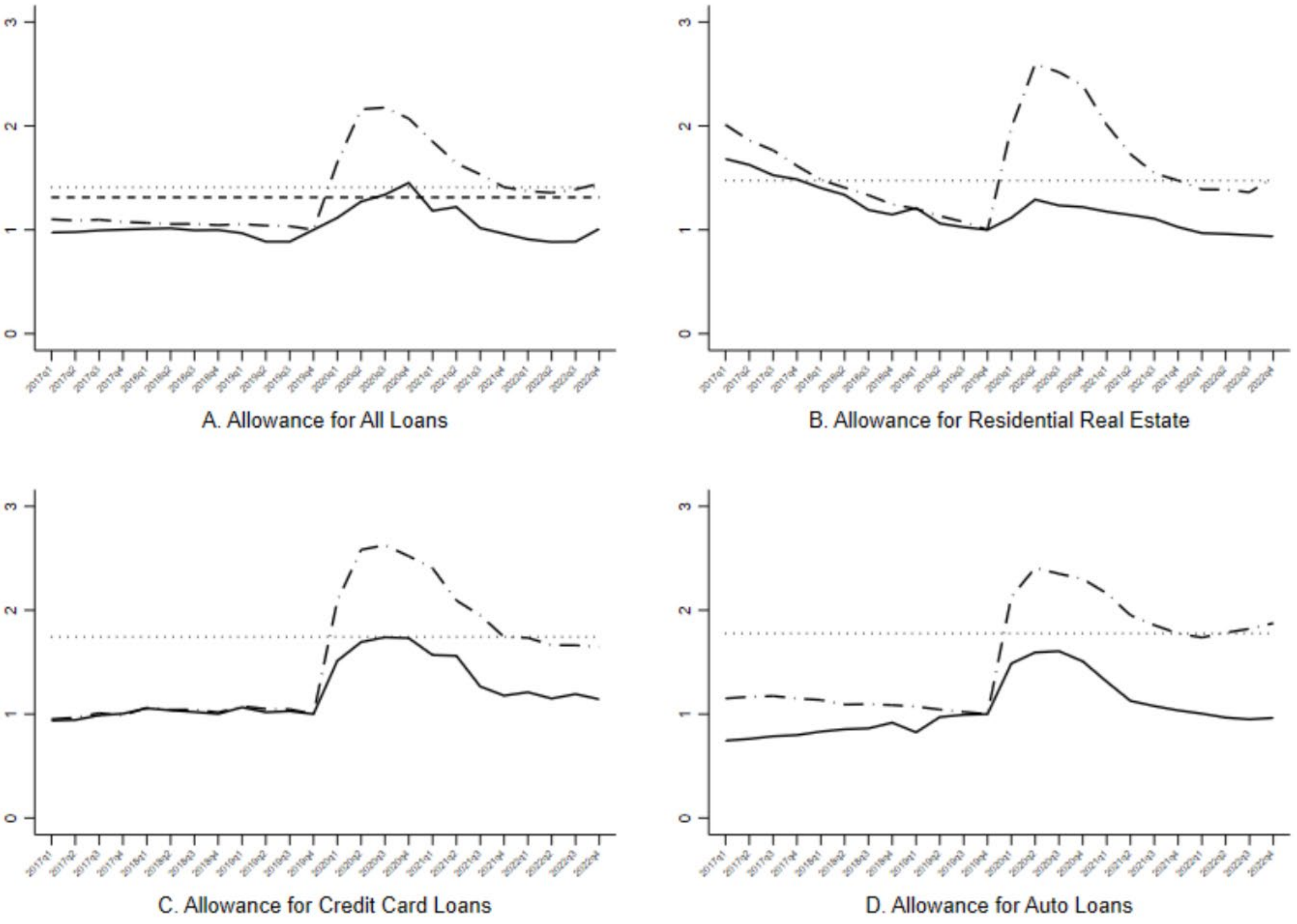
- **CECL will provide added flexibility** to increase allowances and may contribute additional insight into the lending decisions and risks taken by financial institutions.

- **Peak levels of allowances during downturns under CECL will be higher** than under the current incurred loss framework at peak of allowance levels.

- We can expect a **relatively modest average “day one**” impact of CECL, unless the economy is in the early stages of a recession.

- **Not everyone agrees** that **CECL will lead to a decline in lending** during periods of financial stress.

CECL Implementation and the Pandemic – Adopters and Non-Adopters.



Allowances over time as a % of the **base year 2019Q4**, for **adopters** (dot-dash line) and **non-adopters** (solid line).

Also depicted the **first day impact** (horizontal dash line) and the **2021Q1 CECL allowances** (horizontal dotted line).

Data source: https://www.ffiec.gov/

CECL Implementation and the Pandemic – Adopters and Non-Adopters.

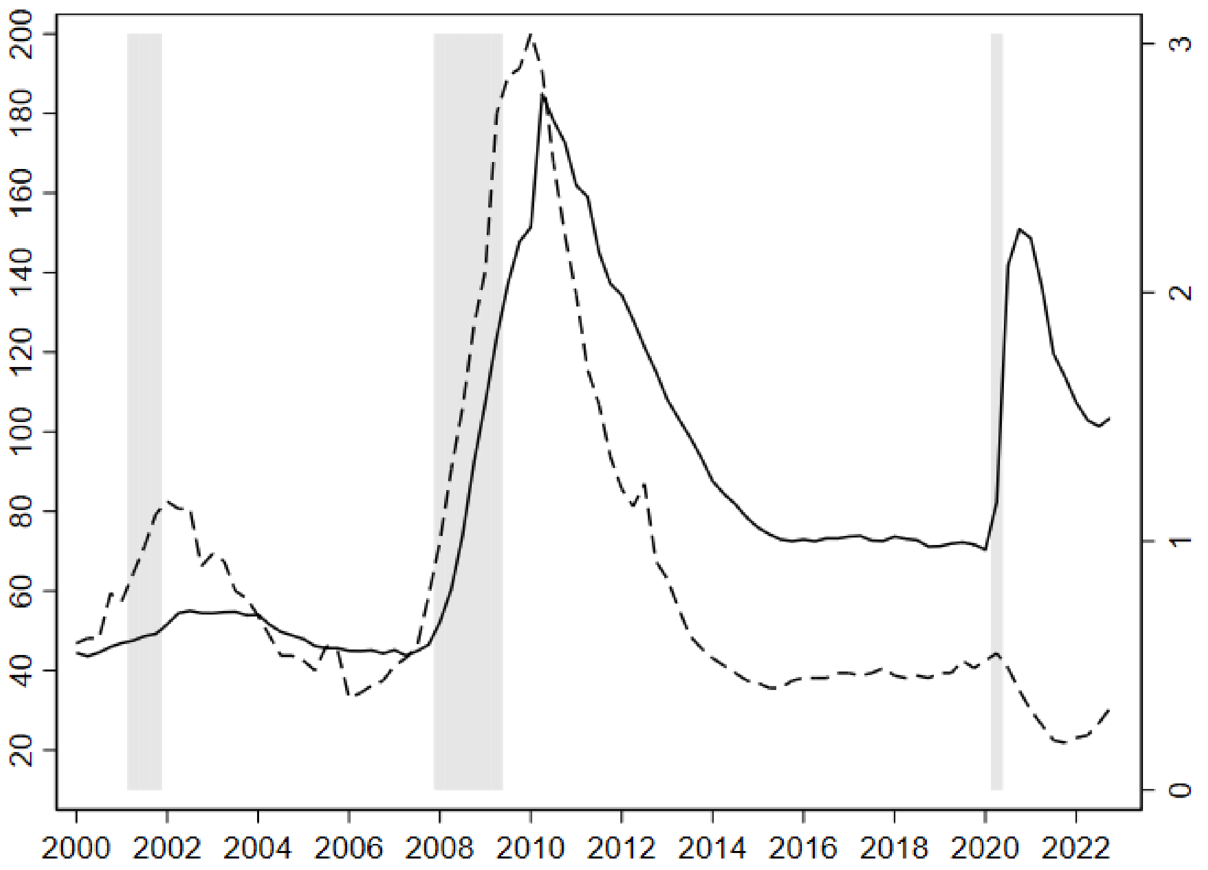
Quarterly ALLL with respect to 2019Q1.

VARIABLES	Residential Loans	Credit Cards	Auto Loans
Non adopters			
2020Q1	1.13	1.49	1.46
2020Q2	1.29	1.68	1.57
2020Q3	1.25	1.71	1.58
2020Q4	1.21	1.69	1.49
2021Q1	1.15	1.53	1.31
2021Q2	1.13	1.54	1.12
2021Q3	1.09	1.22	1.06
2021Q4	1.02	1.13	1.02
2022Q1-Q4	0.99	1.13	0.96
CECL adopters			
2020Q1*CECL	2.01 (0.88)	2.16 (0.67)	2.22 (0.76)
2020Q2*CECL	2.63 (1.34)	2.68 (1.00)	2.66 (1.09)
2020Q3*CECL	2.53 (1.28)	2.72 (1.01)	2.54 (0.96)
2020Q4*CECL	2.45 (1.24)	2.60 (0.91)	2.49 (1.00)
2021Q1*CECL	2.03 (0.88)	2.46 (0.93)	2.27 (0.96)
2021Q2*CECL	1.78 (0.65)	2.13 (0.59)	2.03 (0.91)
2021Q3*CECL	1.6 (0.51)	1.98 (0.76)	1.93 (0.87)
2021Q4*CECL	1.53 (0.51)	1.77 (0.64)	1.84 (0.82)
2022Q1-Q4*CECL	1.45 (0.46)	1.70 (0.57)	1.88 (0.92)
R-squared	0.78	0.96	0.97

- CECL **adopters' allowances responded more quickly** than non-adopters to changes in the economic outlook.
- We observe a **30% first day increase in allowances** for CECL adopters.
- **2020Q2** saw the **peak in CECL allowances**.
- **2020Q3** saw the **peak in non-adopters allowances.**

Data source: https://www.ffiec.gov/

Historical Allowances and Charge Off Rates.

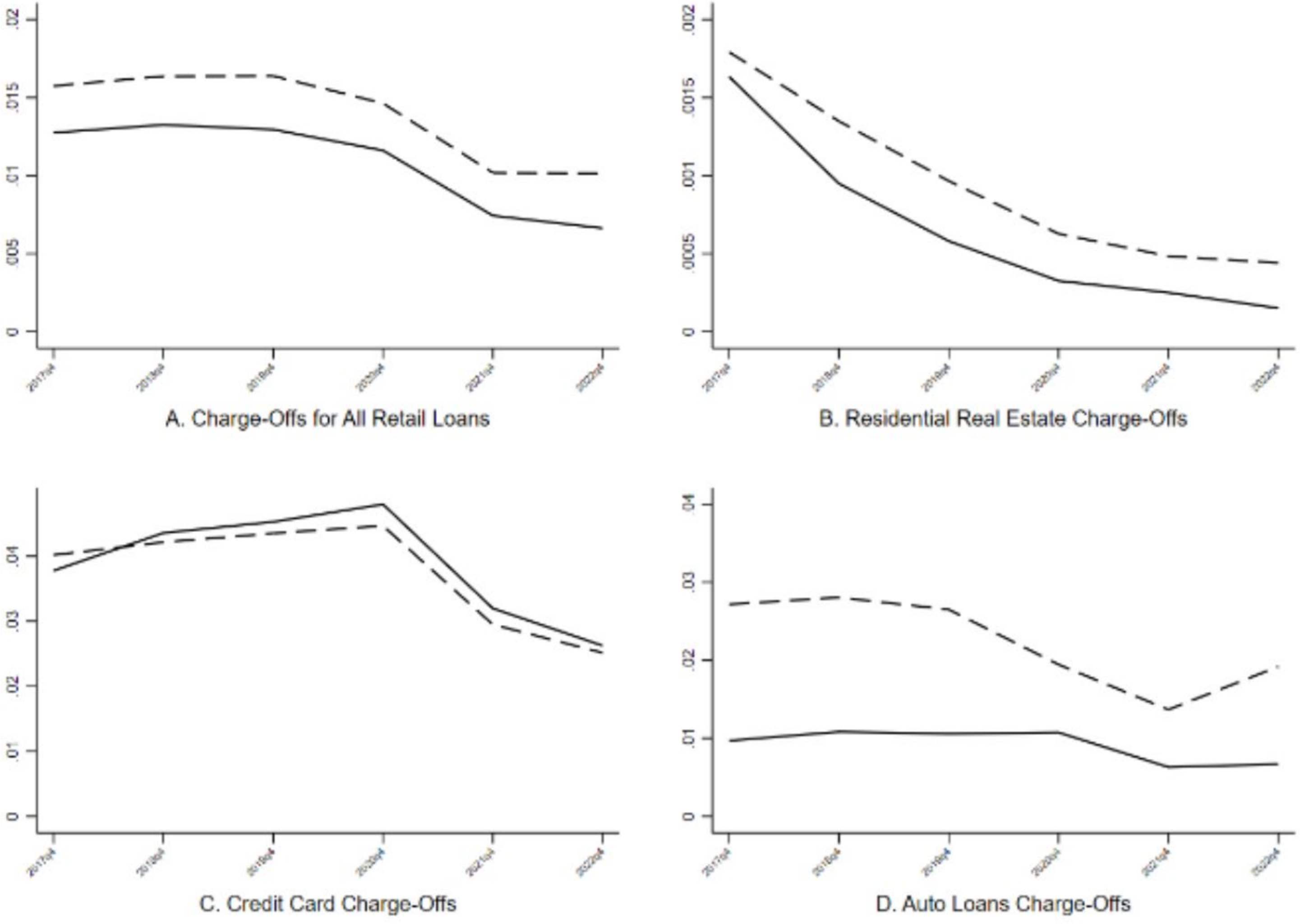


The relationship between ALL and charge-offs was particularly strong during the great recession, in contrast with the period of the pandemic.

The unprecedented government response to the pandemic contributed to a significant difference in performance across two stress episodes.

Data source: https://fred.stlouisfed.org/

Charge off Rates During the Pandemic

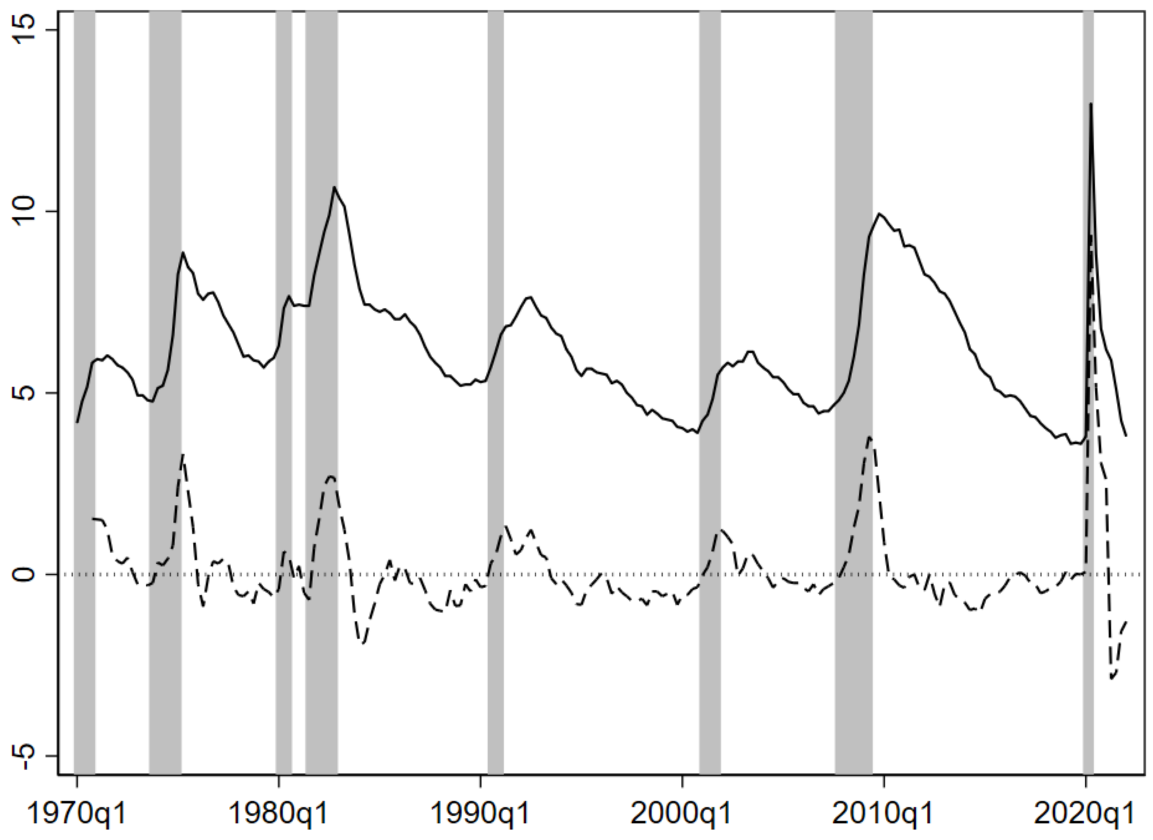


- Charge-off Rates for Retail Portfolios for CECL adopters (dash line) and nonadopters (solid line).
- In hindsight, **Banks provisioned for significant losses that didn't materialize.**
- **The largest impact was observed for CECL adopters.**

Data source: https://www.ffiec.gov/

Dependence on economic forecast makes CECL projections susceptible to forecasting error.

“The only thing we know about the future is that it will be different” Peter Drucker.



Data source: Philadelphia Survey of Professional Forecasters.

The figure depicts **realized unemployment rate** (solid line), and **four quarters ahead forecasting error** (dash line).

How banks adjusted their model outcomes to the new reality of Covid-19?
Some highlights from a recent *BIS newsletter on Covid-19 related credit risk issues*

Credit risk modelling policies and practices

- Banks applied sizeable **judgment-based adjustments** (overlays and judgmental overrides) to both their IRB and provisioning models.
- **Controls and governance** around model adjustments could be improved.
- Credit **data over the crisis period have deviated considerably** from historical patterns and trends.
- This raises a question of **whether and how these data should inform credit models** going forward.
- Both supervisors and banks are grappling with **how to incorporate and reflect data over the Covid-19** period in credit risk models.

[Newsletter on Covid-19 related credit risk issues (bis.org)]

(cont.)

Supervisors observe three main challenges in relation to banks' provisioning models:

- **Controls** around model risk management and data.
- Capturing **economic uncertainty**.
- **Identifying credit deterioration** in vulnerable sectors and borrowers.

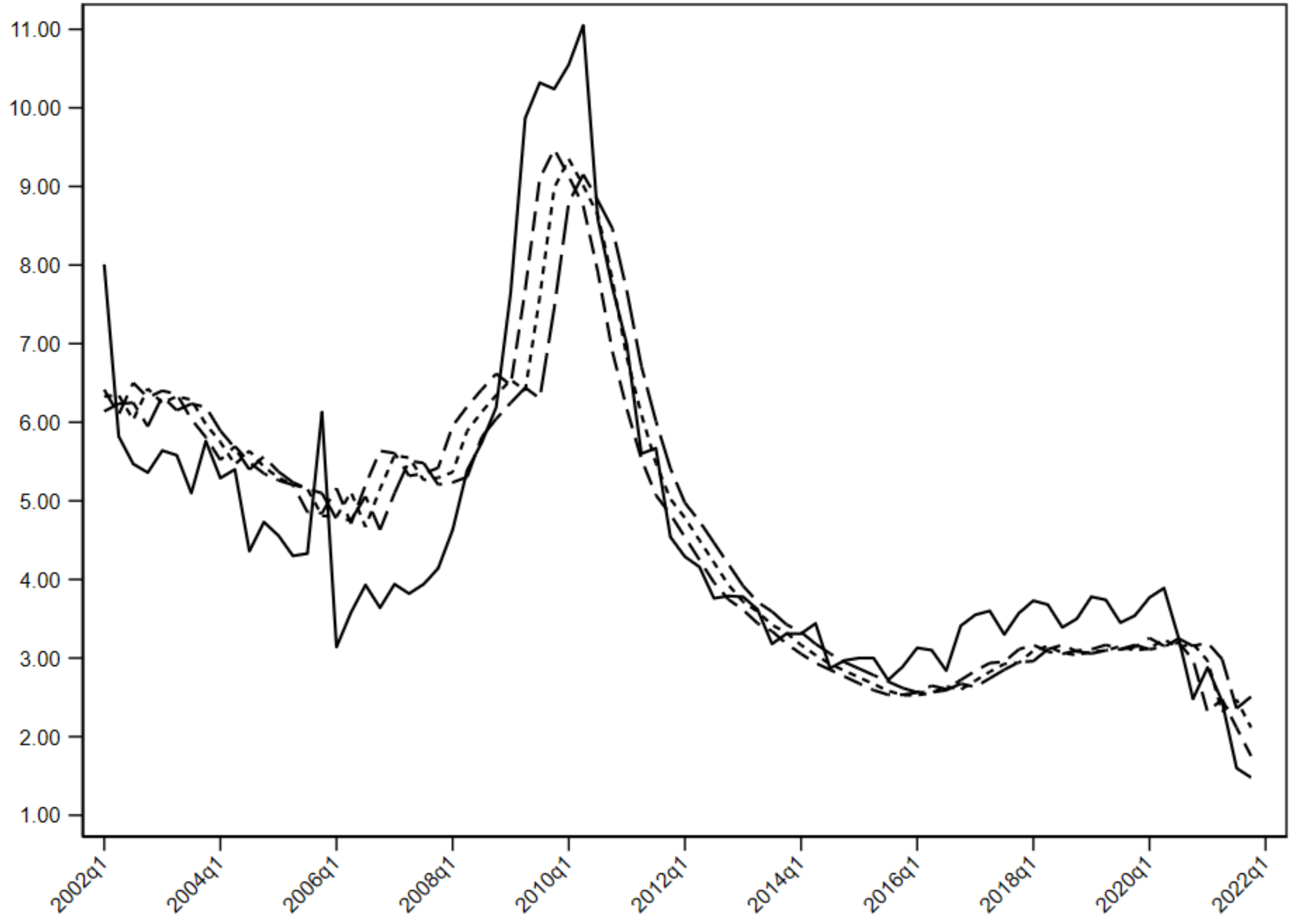
Adopted approaches to model development,

- **Exclusion of Covid-19 related data** (due to the disconnect between macroeconomic variables and default rates).
- **Utilization of new data** collected during Covid-19 with the application of judgmental overlays to counteract any changes in existing relationships (eg macroeconomic variables vs defaults)
- **Enhancing the infrastructure** and data feed to ensure the relevant data are fully understood and properly integrated into analysis of decision-making systems.

Not all relationships “broke down” during Covid-19.

Note: realized charge-off rate (solid line), fitted charge-off rate (dotted-lines). In sample 2002-2019, out of sample 2020-22. Models estimated with 2, 3, and 4 quarters delinquency rate lags.

Credit Card Charge-off Rate fitted to delinquency rate lags.



Data source: https://fred.stlouisfed.org/

Why Forecast Accuracy Deteriorates During a Crisis?

Hendry and Mizon (2014) classify unpredictability in forecasting into three categories:

(1) Anticipated **stochastic variation in forecast**. (Intrinsically unpredictable)

(2) Unexpected **instances of outliers**, or “black swans.” (Instance unpredictability)

(3) Unexpected **persistent “regime shifts.”** (Extrinsic unpredictability)

The two recent crises are arguably examples of 3 (extrinsic unpredictability) :

Great recession: unprecedented decreases in home prices.

Pandemic: unprecedented levels of macroeconomic stress and public assistance.

A Simple Loss Forecasting Framework.

For illustrative purposes consider a conceptually simple loss framework:

$$L_k = \psi_k(s, m_k) + \epsilon_k, \; k = 1, \ldots, T$$

with,

L representing loss projection

m representing the *"macroeconomic forecasts" projections*

s *representing relevant portfolio characteristics*

The loss projection can then be computed as,

$$\hat{L}_k = \hat{\psi}_k(s, \hat{m}_k)$$

Forecast Accuracy: Mitigating the Impact of Macroeconomic Forecasts

The inherent uncertainty of macroeconomic forecasts generally increases in challenging economic environments.

Supportable forecast horizons are likely shorter in high uncertainty periods.

Forecast uncertainty can be incorporated into CECL projections, for example by considering multiple scenarios with the importance (weight) assigned to different scenarios commensurate with the level of confidence on forecasts.

Forecast Accuracy: Mitigating the Impact of Model Error.

The typical sources of model misspecification, **functional form misspecification** and **omitted variables**, were present during the pandemic.

Models trained with historical (great recession) data generated inaccurate forecasts during the pandemic. Forbearance & government programs induced long term shifts in historical relationships,

$$L_k = \psi_k(s, m_k) + \in_k \quad \Longrightarrow \quad L_k = \Phi_k(s, m_k, g_k) + \in_k$$

Φ_k may differ substantially from ψ_k.

g_k represents government programs omitted from pre-pandemic models.

Mitigating the Impact of Model Misspecification Error under extrinsic unpredictability conditions.

- Model misspecification error can lead to biased projections, even in the case of accurate economic forecasts.

- An understanding of the sources of model misspecification and simple econometric principles can offer useful guidance to address model "misspecification" shortcomings in the short run, and to build more robust models in the long run.

- As a rule of thumb, model bias increases with the severity of misspecification.

- Econometric theory suggests that model factors that have the largest correlations with relevant unaccounted factors, or omitted variables, will have the largest impact on misspecification bias.

Mitigating the Impact of Model Misspecification Error under extrinsic unpredictability conditions.

- **Over-reliance on a single model** is probably **not an optimal strategy** in times of stress. In fact, while models conditional on macroeconomic factors generally performed poorly, not all relationships "broke down" during COVID-19 as we will argue in our empirical example.

- **simple models can act as benchmarks or early warning models to primary models**, can offer guidance when overrides or overlays are applied to primary models, or can serve as a platform to open a dialogue with senior managers, auditors, or regulators.

- **Simple model specifications that leverage robust sources of information,** and downplay potentially biased information, **may prove to be useful** after a shock.

- **It may also be helpful to analyze potential divergences between early indicators of stress and model predictions of loss**. This can serve as an early warning of model performance bias.

Climate risk, another area where Government assistance can impact model predictions.

Evidence supports the significant impact of government assistance and insurance.

- Flood insurance largely mitigates the negative effect of the natural disaster.
- Medium-size natural disasters are less likely to result in long-term government recovery funds, resulting in larger declines in credit scores.

KATRINA - COSTS AND PUBLIC/PRIVATE RECONSTRUCTION AID (in billions)	
ESTIMATED DAMAGE COSTS	108
RECONSTRUCTION AID:	114+
Private and public insurance	57.1
Philanthropy	6.5
Government assistance	50.8

Note: The table summarizes disaggregated information from Bleemer & van der Klaauw (2019).

An Application to Consumer Finance Portfolios.

We illustrate our views highlighted in previous slides by introducing an econometric framework that is nimble, and adaptable, and consistent with the CECL framework.

We focus our attention on consumer finance portfolios which typically comprise many millions of anonymized loans (personal loans, mortgages, auto loans, credit card loans, student loans).

In our empirical application the focus will be on auto loans.

We will employ data from the FRBNY Consumer Credit Panel/Equifax (CCP) and specifically its associated Auto Tradeline panel data.

The focus will be on 9 quarter default and expected lifetime default as the data has no information on loan loss given default.

Simple models don't always require a compromise.

Consider a consumer loan a_i with associated default distribution Bernoulli(p) or B(1,p).

A segment of iid loans with the same default probability will have aggregated default distribution of the form,

$$\sum_{i=1}^{n} a_i \sim B(n,p) \sim \text{Poisson}(\lambda) \text{ with } \lambda = np \text{ (approx.)}$$

We can use this argument as a justification for using the Poisson distribution for the purpose of analyzing the number of defaults in an homogeneous segment of loans.

For the purpose of estimation, the model will be parametrized as usual, by considering $\lambda_X = \lambda(X, M)$. With X observable heterogeneity and **M macro drivers**.

We simplify the framework by dividing the space X into homogeneous segments with

$$\lambda(X, M) = \lambda_X(M) \text{ and } \lambda_X \text{ constant within segments.}$$

We can do this by using expert judgment, or unsupervised/supervised ML techniques.

STEPS OF THE AGGREGATED MODEL METHODOLOGY:

STEP 1: Segmentation. We can do this by using expert judgment, or unsupervised/supervised ML techniques. Not that different from the standard strategy of discretizing important variables like credit score to deal with non-linearities.

STEP 2: Estimate Poisson models for the number of defaults in each performance period t = 1,…,T for each segment S with N_s loans.

STEP 3: Aggregated defaults can be estimated from the period specific Poisson-estimated defaults

$\widehat{n_{s1}} + \ldots + \widehat{n_{sT}}$ and default probabilities is defined dividing by the segment specific number of accounts N_S

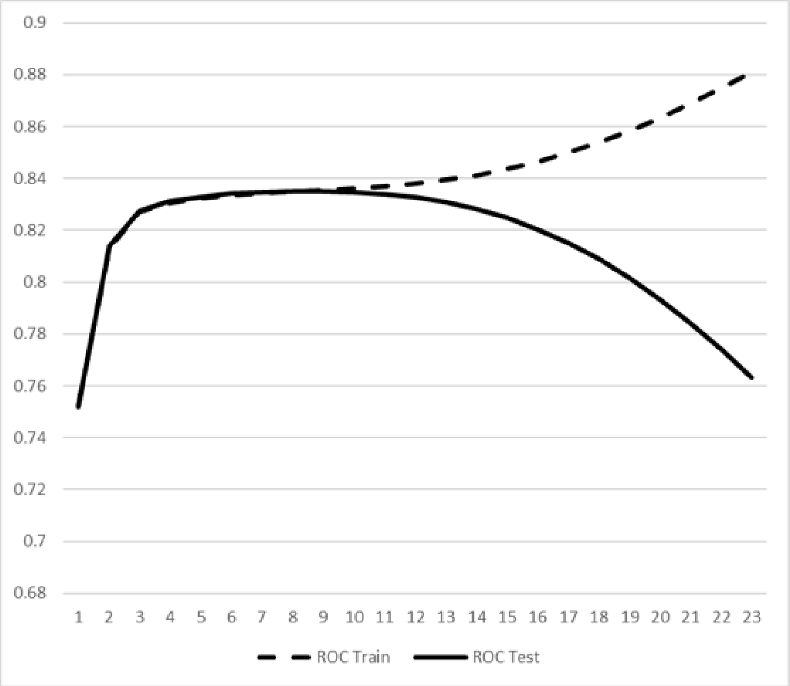
Estimation can be defined in a single line of code irrespective of the number of segments.

```
gsem (n1 <- f1) ...  (nt <- ft), poisson exposure(n) ginvariant(none) group(s)
```

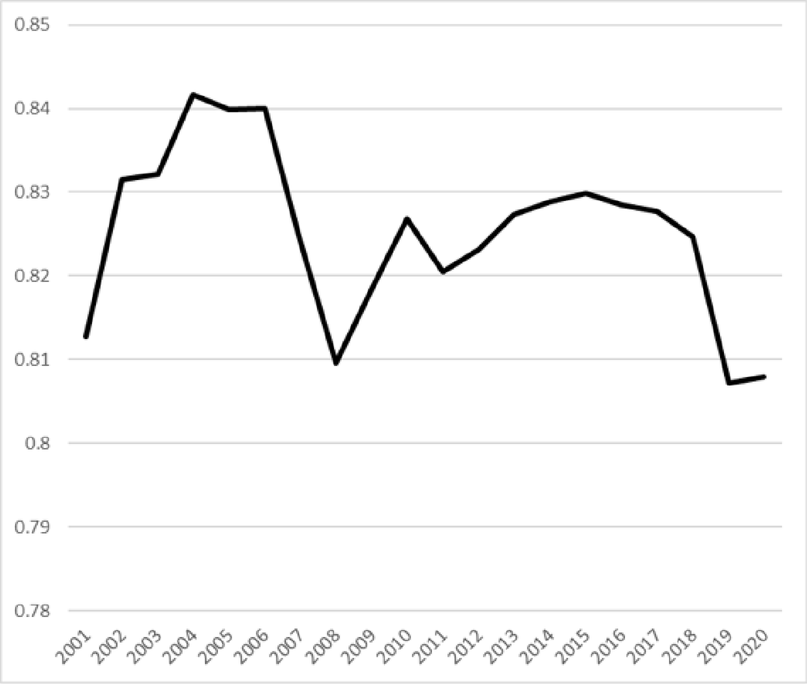
Data dimension: Num. Segments x Num. Time Periods x Num. Geographic Areas (independent of N loans!)

Estimation can be conducted in seconds irrespective of sample size N! Thus, allowing for **search of best model** specification and **management of many models simultaneously**, without significantly increasing complexity.

Segmentation - ROC performance across models and over time.



a.- ROC performance across models.



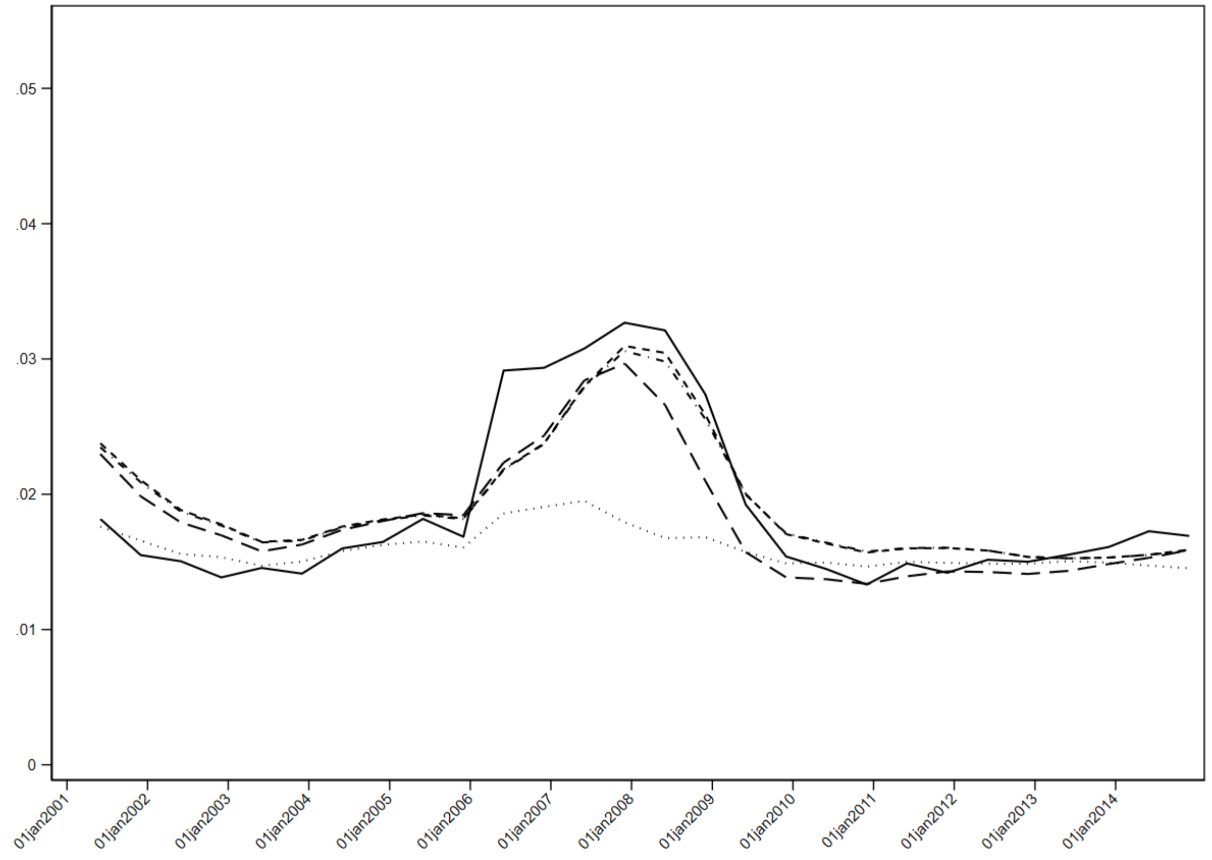
b.- Two-year ROC performance over time.

- ROC does not improve significantly for a decision tree classifier of the two-year forward-looking default, as the maximum dept of the tree increases beyond 3 (test data).
- For a selected segmentation scheme, ROC performance deteriorated somewhat during the great recession and again during Covid but continued to rank order reasonably well over the years.

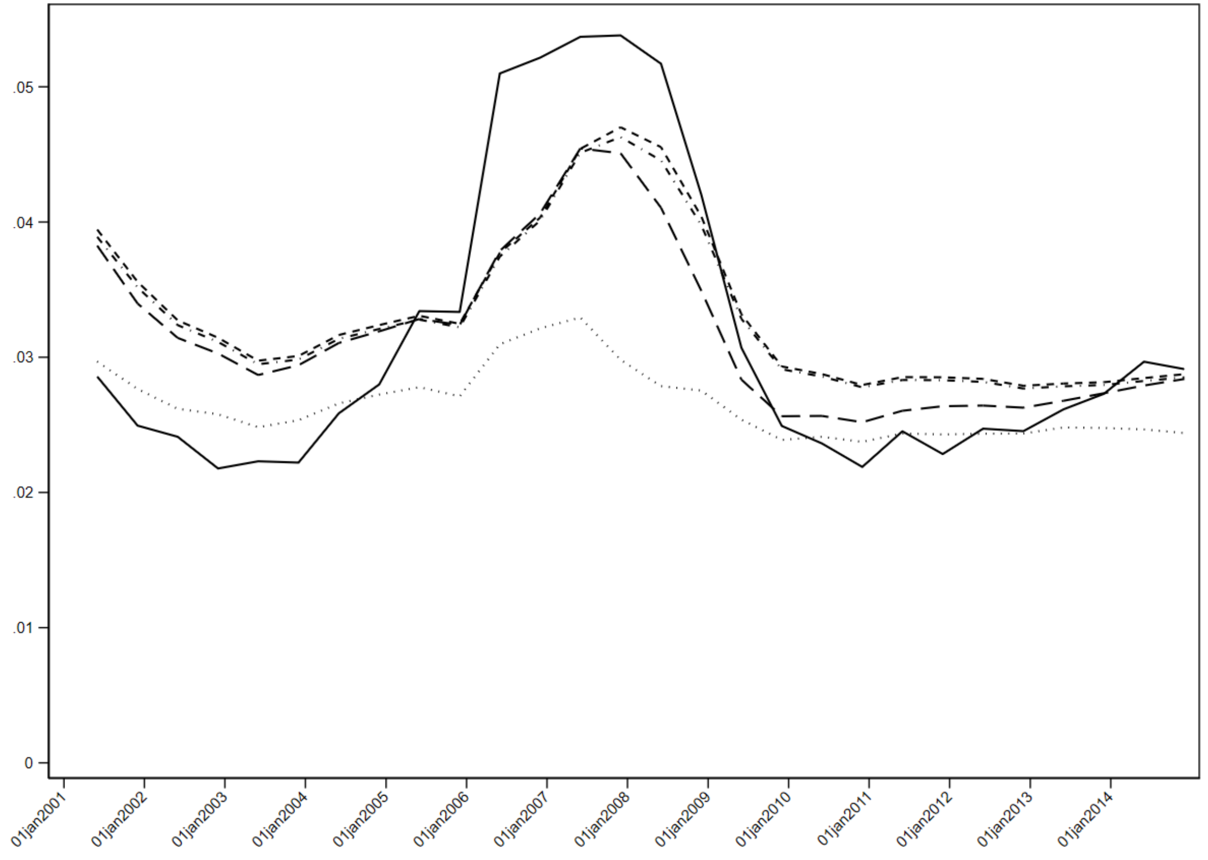
Sources: Calculations using FRBNY Consumer Credit Panel/Equifax (CCP)

Model Performance During the Great Recession.

Nine Quarters Cumulative Default Rates Across Cohorts.



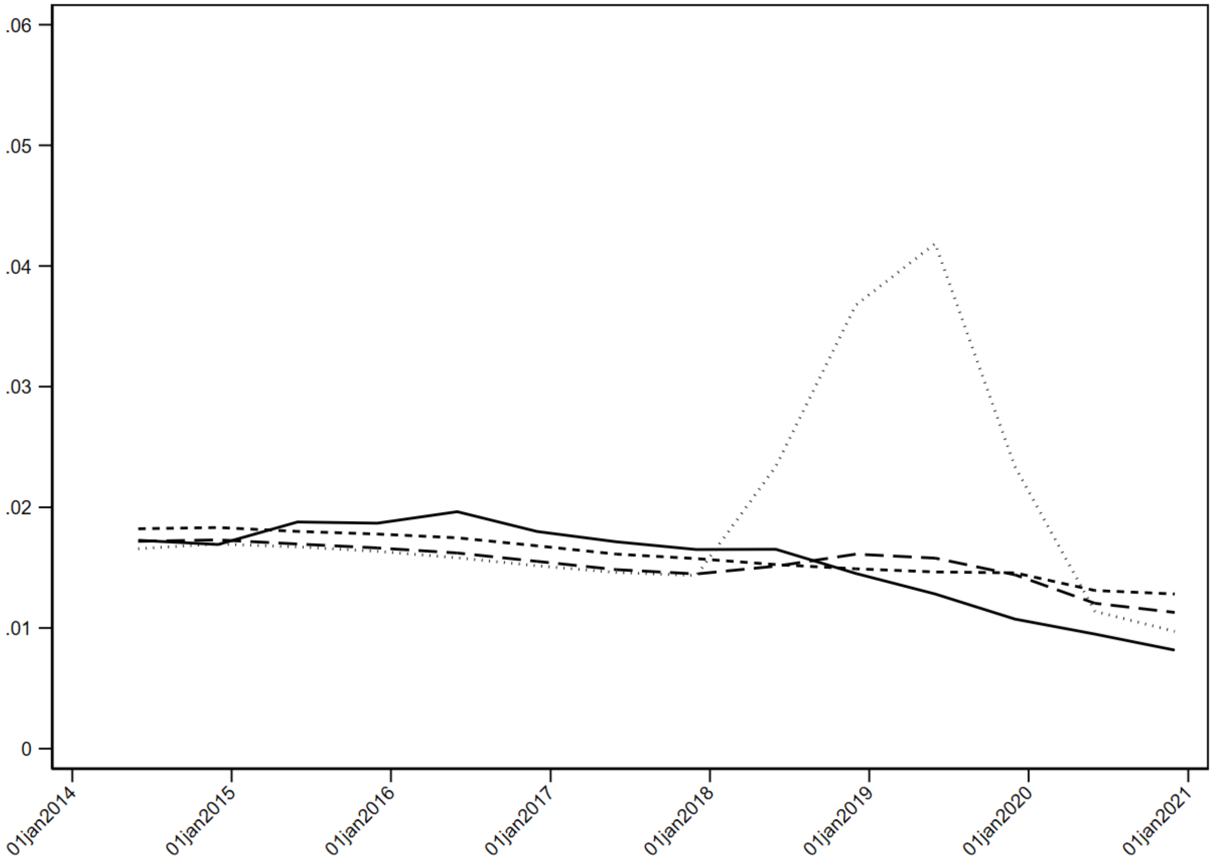
Lifetime Cumulative Default Rates Across Cohorts.



Sources: Calculations using FRBNY Consumer Credit Panel/Equifax (CCP)

Realized values (solid line),
projections for different model specifications (all other)
Models without macro drivers (dotted line)

Nine Quarters Cumulative Default Rates Across Cohorts, Including the Covid 19 Period.



Sources: Calculations using FRBNY Consumer Credit Panel/Equifax (CCP)

The figure depicts,

- Realized nine quarters cumulative default rates across cohorts (solid line)

As well as forecasted values for models estimated with data including nine quarters of performance from the

- 2001-17 cohorts (dotted line),
- 2001-20 cohorts (long dash line),
- and 2001-17 cohorts without macro variables (dash line).

Some challenges to the adoption of flexible and proactive methodologies.

McKinsey & Company (2022): “Model risk management 2.0 evolves to address continued uncertainty of risk-related events.”

In the United States, initial validation for **Tier 1** models takes **12 weeks** on average, while **Tier 2 and 3 models** take *six and four weeks*, respectively. For periodic validation, the timelines are on average seven weeks, five weeks, and four weeks, respectively.

A majority of MRM teams are planning to work closely with the first Line of Defense to assess the impact of the COVID-19 pandemic on models and standards, with a focus on model performance-monitoring activities.

US banks have seen as much as 25 percent jump in number of models since 2019.

US banks are focused on automation of MRM workflows, as well as managing validation frequency for some models.

Parting thoughts – Quantification Challenges

Recent experience supports research claims prior to CECL implementation: procyclicality, flexibility & higher peak allowances during a downturn, increased sensitivity of allowances to model forecasts under CECL.

We leverage theory in search for insights on how to build more robust model infrastructures and troubleshoot models in times of crisis. Some insights include,

- Avoid overreliance on single models.
- Focus on adaptability of model infrastructure in times of crisis.
- Consider flexible forecasts and forecast horizons.
- Leverage multiple models and understand their strengths and weaknesses.
- Consider redevelopment or redesign of models (it helps to be nimble).

Parting thoughts – Quantification Challenges

When building models and model infrastructures it is important to look beyond the statistical framework and to consider <u>resiliency and adaptability to new shocks</u>.

We illustrate these ideas with a simple empirical framework that,

Describes simple models without compromising performance.

Allows for easy redeveloped and redesigned of models.

Allows for quickly deployment across large consumer finance portfolios.

Regulated institutions face specific validation challenges. Thus, it is important to have strategies in place in anticipation of periods of crisis.

Many Thanks!