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A Consumer Finance Perspective

José J. Canals-Cerdá
Federal Reserve Bank of Philadelphia Supervision, Regulation, and Credit Department

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Model Risk Under CECL: A Consumer Finance Perspective

By José J. Canals-Cerdá[1]

Abstract

We examine the challenges of economic forecasting and model misspecification errors confronted by financial institutions implementing the novel current expected credit loss (CECL) allowance methodology and its impact on model risk and bias in CECL projections. We document the increased sensitivity to model and macroeconomic forecasting error of the CECL framework with respect to the incurred loss framework that it replaces. An empirical application illustrates how to leverage simple machine learning (ML) strategies and statistical principles in the design of a nimble and flexible CECL modeling framework. We show that, even in consumer loan portfolios with tens of millions of loans, like mortgage, auto, or credit card portfolios, one can develop, estimate, and deploy an array of models quickly and efficiently, and without a forecasting performance penalty. Drawing on more than 20 years of auto loans data and the experience from the Great Recession and the COVID-19 pandemic, we leverage basic econometric principles to identify strategies to deal with biased model projections in times of high economic uncertainty. We advocate for a focus on resiliency and adaptability of models and model infrastructures to novel shocks and uncertain economic conditions.

JEL Codes: G01, G21, G28, G50, M41

Keywords: CECL, Allowance for Loan and Lease Losses, Accounting Regulations, Model Risk

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I. INTRODUCTION

The Allowance for Loan and Lease Losses (ALLL) is an estimate of credit losses used to reduce the book value of loans and leases to the amount that a bank expects to collect. The ALLL is of great importance to bank management, investors, and regulators. The ALLL approach over a 40-year period was the incurred loss methodology. Under the incurred loss approach, the allowance was established to cover losses that are probable and estimable as of the reserve calculation date.[2] In the aftermath of the 2007–09 Great Recession, the incurred loss methodology was criticized for its "failure to fully recognize existing credit losses earlier in the credit cycle."[3] In an attempt to address identified shortcomings with the existing approach, in 2016, the Financial Accounting Standards Board (FASB) introduced the current expected credit loss (CECL) framework, a novel approach for computing the ALLL. CECL transforms the loan loss provisioning methodology by considering lifetime loan losses and by incorporating forward-looking forecasts of economic conditions into the forecast of expected loss.[4] The novel CECL methodology became effective for most U.S. Securities and Exchange Commission (SEC) filers after December 15, 2019, with the exception of smaller reporting companies. The group of initial CECL adopters included the most complex financial institutions in the United States, other companies were required to adopt CECL by January 1, 2023.

In this paper, we analyze CECL challenges in times of heightened economic uncertainty, drawing on lessons from the Great Recession and the COVID-19 pandemic. We examine challenges arising from uncertain economic forecasts and the effects of government interventions on CECL projections. Leveraging a simple statistical framework, we investigate problems of forecasting and model misspecification bias, providing practical insights for navigating future crisis episodes. The focus of the CECL framework on the projection of lifetime loan losses — and its reliance on economic forecasts — increases the sensitivity of the allowance to economic forecasting and model error. Banks reported challenges of CECL implementation in

[2] See Statement of Financial Accounting Standards 114.

[3] See the Financial Stability Forum (2009) report.

[4] Additional information is available at www.federalreserve.gov/supervisionreg/topics/faq-new-accounting-standards-on-financial-instruments-credit-losses.htm.

their public disclosures, including operational and framework complexity challenges and extensive data requirements. We observe differences in the experience of CECL adopter and nonadopter financial institutions during the initial adoption phase, which coincided with the early months of the COVID-19 crisis. Allowances from CECL adopters increased faster early in the pandemic and reached a much higher peak when compared with nonadopters. In contrast, charge-off rates during this period decreased with respect to the already record-low levels of recent years, generating a historically unparalleled gap between allowances and charge-offs. Financial institutions faced with highly atypical macroeconomic conditions and underperforming models resorted to judgment-based adjustments to their provisioning projections. This experience underscores the significant challenges to the CECL framework in times of highly uncertain economic environments typical of crisis episodes. It is important to draw lessons from past crises and to take appropriate steps to strengthen the fundamental allowance framework.

In order to analyze potential CECL challenges in times of high economic uncertainty, we construct a simple modeling framework based on sound statistical principles. Our approach is deployed in two steps. First, we utilize simple ML techniques to segment a loan portfolio into sets of loans with broadly homogeneous risk profiles, and second, we employ standard statistical methods across segments to model lifetime CECL projections, conditional on macroeconomic forecasts. Our framework is simple without compromising performance. It allows for quick and easy development, redesign, and deployment of models, irrespective of the size of the portfolio considered and, because of its simplicity, it can easily accommodate multiple models. For these reasons, the approach is particularly valuable in consumer finance portfolios, like personal loans, student loans, mortgages, or credit card loans, where the typical loan portfolio can comprise many millions of loans.

Our empirical analysis employs granular anonymized credit bureau loan level data from the FRBNY Consumer Credit Panel/Equifax (CCP) and considers an application to auto loans, which is an important lending market that has not received the same level of attention as other forms of lending in the consumer finance literature (i.e., mortgage or credit card lending). A simple extension to credit card portfolios, leveraging publicly available aggregated data, adds robustness to the insights derived from our empirical exercise. Auto and credit card lending represent, after mortgages, the second- and third-largest forms of nongovernment lending to consumers. At the end of 2024, auto loans represented $1.6 trillion in consumer lending, with 60 percent of U.S. adults with a credit report having an auto loan; credit cards represented close to $1.2 trillion.[5]

Leveraging the simplicity of our modeling framework, we analyze potential problems of forecasting bias and model misspecification that can impact CECL implementation during periods of high economic uncertainty. We analyze more than 20 years of portfolio performance, encompassing the Great Recession and the COVID-19 pandemic. We observe that model performance deteriorates significantly in periods of crisis with associated uncharted economic environments. Two primary sources of model performance deterioration relate to errors in economic forecasts and the inability to anticipate the level and impact of government policy response, which can significantly lessen credit risk in consumer finance and can lead to model misspecification errors in CECL projections.

Economic uncertainty increased significantly as a result of COVID-19 (Altig et al. 2020). Periods of heightened economic uncertainty have traditionally been accompanied by significant government responses. The COVID-19 crisis precipitated unprecedented levels of government assistance across multiple complex public assistance programs that evolved over time. Assistance was extended by federal, regional, and local governments and included individual cash payments, extensions of unemployment benefits, assistance to small businesses and corporations, as well as assistance to communities, among others.[6] An important insight from the analysis in this paper relates to the inherent difficulty associated with empirically ascertaining the impacts of government interventions implemented in periods of crisis. This is particularly the case for the forward-looking projections of lifetime credit loss under CECL. First, it is important to recognize the endogeneity in the relationship between the perceived severity of a crisis and the accompanying level of government assistance. On the one hand, as the perceived or expected economic severity evolves, it can trigger additional forms of government intervention. On the other hand, significant government intervention, or even the promise of future interventions,

[5] 2024Q4 FRBNY Consumer Credit Panel/Equifax.
[6] See the CARES Act: https://www.congress.gov/bill/116th-congress/house-bill/748.

can alleviate economic stress. As an example, dozens of government interventions and forbearance programs were implemented in the area of student loan financing, expanding over a four-year post-COVID period.[7] Government forbearance programs were also implemented in other areas of consumer finance, primarily mortgages, and these efforts were accompanied by similar initiatives among private lenders in areas like mortgage, auto, and credit card lending. Finally, other forms of government intervention, like the Term Asset-Backed Securities Loan Facility (TALF) program, may have also contributed to well-functioning consumer finance markets and the availability of credit.

Government interventions can lead to a breakdown in the traditional relationships between economic variables and credit risk. Guidance from econometric theory can offer insights that can help alleviate the impact of these government interventions on biased model forecasts. We observe that leveraging insights from a variety of model specifications can be fruitful, particularly in times of crisis. We observe that model performance can improve significantly when models are re-estimated with additional data that includes some exposure to the novel economic environment. We also observe that model performance may not deteriorate homogeneously across risk segments, so certain segments can potentially act as an early warning for more widespread underperformance. Furthermore, CECL long-run projections by design average out economic cycles to a certain extent, although short-term and medium-term loss projections are primary drivers of CECL allowances for cards and auto portfolios.

The next section introduces the CECL framework in greater detail, analyzes challenges of adoption, and provides a brief review of the growing related literature. Section three analyzes the challenges that firms faced with the implementation of CECL around the time of COVID-19 and then analyzes conceptually the impact of economic forecasting error and model misspecification error on CECL allowances. Section four introduces a simple empirical framework for CECL implementation with an application for auto loans as a particular example of a consumer finance portfolio. Section five discusses empirical findings and lessons learned on how to mitigate potential CECL projection bias in times of high economic uncertainty. Section six concludes. An

[7] https://www.congress.gov/crs_external_products/IF/PDF/IF12136/IF12136.6.pdf

appendix provides some additional background on regulatory guidance regarding CECL implementation.

II. The CECL Framework, Inception and Adoption

In the next subsections, first, we briefly describe the incurred-loss framework, its shortcomings identified during the Great Recession, the CECL framework that replaces it, and initial CECL implementation challenges among financial institutions. Second, we analyze the performance of both allowance frameworks with a special focus on the period of the COVID-19 pandemic. Finally, we review the growing research literature investigating potential strengths and weaknesses of the CECL framework.

A. The Incurred-Loss Framework, the CECL Framework and Its Implementation

Under the incurred-loss framework, potential future losses that are not deemed probable should not be accounted for. This is the case even if it is reasonable to anticipate future losses that are not categorized as probable at present time, perhaps as a result of expected future credit risk deterioration resulting from a worsening in economic conditions. Existing research indicates that banks with longer delays in loss recognition tend to contract their balance sheets and reduce their lending more during recessions (Beatty and Liao, 2011; Bushman and Williams, 2012). By delaying the recognition of loan losses during the Great Recession, the incurred-loss framework contributed to the buildup of allowances amid the stress period. As a result, it may have contributed to a decrease in bank lending and to the overall procyclicality of the financial system. Bischof, Laux, and Leuz (2021) provide evidence indicating that managerial reporting incentives may have contributed to delays in the recognition of losses ahead of the 2007–09 crisis under the incurred-loss framework. Furthermore, research by Harris et al. (2018) indicates that measures of credit risk readily available in financial statements provide incremental information that can contribute to better predictions of future losses relative to the incurred-loss framework. Thus, a forward-looking allowance allows for earlier recognition of anticipated losses and may provide useful information for analysis.

The Financial Stability Forum (FSF) in its 2009 report on procyclicality in the financial system indicated that earlier recognition of loan losses could help lessen procyclicality while enhancing the consistency of the information provided to investors. The report stated that accounting standard setters should consider alternative approaches to the incurred-loss framework that incorporate a broader range of available credit information, reduce or eliminate disincentives for establishing appropriate provisions, and improve financial disclosures. Various stakeholders requested that accounting standard-setters work to enhance the loan loss provisioning methodology to incorporate forward-looking information. In June 2016, the Financial Accounting Standards Board (FASB) issued an accounting standard update (ASU 2016-13) that introduced the CECL framework.

CECL represents a significant departure from the incurred-loss framework that it replaces. CECL is built on the notion of forward-looking estimates of expected loan credit loss based on relevant information about past events, including historical experience, current conditions, and reasonable and supportable forecasts that affect the collectability of loans. Under CECL, institutions are expected to reserve for lifetime losses on loans at the time the loans are originated.[8] It also requires enhanced disclosures.[9] CECL is nonprescriptive about the loss projection methodology that should be employed or about the economic projections that should be considered. However, it prescribes reasonable and supportable forecasts over a reasonable time frame, which can be less than the life of the loan, and convergence to long-run economic conditions after that. At a very high level, CECL considers lifetime losses on a static portfolio. In the case of credit cards and similar lending products where the bank can unconditionally cancel future line draws, CECL does not consider future drawdowns when accounting for potential future losses (Canals-Cerdá, 2020). The CECL standard became effective after December 15, 2019, for most SEC filers, including complex bank holding companies (BHCs), and other companies were required to adopt CECL by January 1, 2023.

A review of public financial disclosures from a sample of large U.S. banks provides insights into CECL implementation challenges faced by financial institutions. Specifically, we review public

[8] Banking regulators have issued Implementation and transition guidance. See the Board of Governors of the Federal Reserve System (BOG), www.federalreserve.gov/supervisionreg/topics/accounting.htm or www.federalreserve.gov/newsevents/pressreleases/files/bcreg20200826a2.pdf for recent guidance.

[9] CECL applies to every organization required to issue financial statements in compliance with U.S. GAAP. Following U.S. GAAP is required by the Federal Deposit Insurance Act, which notes 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.

financial disclosures from a sample of 10 U.S. banks with assets above 100 billion and a significant consumer finance presence, or about one-third of all U.S. banks with more than 100 billion in assets.[10] We review public annual reports for 2019–21 along with quarterly earning calls transcripts for the period 2019Q4–2020Q4.

As banks finalized their CECL implementation framework in 2019Q4, reported challenges included extensive data requirements, operational challenges related to framework complexity, validation and audit, as well as the need to integrate CECL with internal stress tests. Challenges regarding the need for a level of judgment around certain aspects of CECL were also highlighted. For example, judgment decisions related to the remaining expected life of a loan across different loan categories, or the choice of reasonable and supportable forecasts, which in some cases require weighting across multiple economic forecast scenarios. Under the new allowances framework, changes in forecasted economic conditions can result in greater variability in allowances from quarter to quarter. CECL can also increase reserves faster and to a higher level in an economic downturn. It was also indicated that lifetime loss provision requirements may impact lending decisions and underwriting standards over the business cycle. Specifically, a worsening economic outlook could lead to a rapid build-up in reserves and tighter lending standards, possibly having a contractionary effect. Reported potential benefits of CECL included more informative financial disclosures for investors, owing to the recognition of lifetime credit risk, and more data-driven and forward-looking risk management practices. Benefits highlighted in bank disclosures are in line with the objectives of the Financial Accounting Standards Board (FASB), while highlighted challenges broadly align with research detailed later in this section. Model risk was also identified as an area of concern in bank reports, stemming from an increased reliance on models and forecasts.

B. Descriptive Analysis of the Incurred-Loss and CECL Frameworks

Financial Institutions implementing the CECL framework coexisted with nonadopter institutions over the period 2020–2023. As a result, both allowance frameworks can be analyzed side-by-

[10] See https://www.federalreserve.gov/releases/lbr/current/ for a list of U.S. banks above 300 million in assets.

side. We start by examining allowances and charge-offs for all commercial banks over the period 2000–22 at the aggregate level. As figure 1 indicates, the relationship between ALLL and charge-offs was particularly strong during the Great Recession, with charge-off rates increasing significantly and more rapidly initially than the ALLL, which did not peak until early 2010. In contrast, charge-offs decreased to record-low levels during the 2020–22 period, while allowances increased significantly during the initial phase of the pandemic and then decreased significantly over the next few quarters, until they stabilized in 2022. Charge-off rates during the COVID-19 pandemic decreased with respect to the already record-low levels of recent years. This difference in charge-off and allowance performance across two stress periods highlights the importance of analyzing the impact of economic forecasting error, as well as the unprecedented fiscal and monetary policy responses experienced during the pandemic, and its impact on the performance of consumer finance portfolios and the allowance framework.

Using publicly available consolidated financial statements for holding companies reporting form FR Y-9C, Figure .a depicts the behavior of allowances for CECL adopters and nonadopters, with allowances reported as a percentage of the allowances in the fourth quarter of 2019.[11] The dash line represents the first-day CECL transition amount, resulting in an increase in allowances of about 30 percent on average. The dotted line denotes CECL allowances in the last quarter of 2021, which is representative of a period with low unemployment and low charge-off rates. Allowances remained broadly unchanged during the 2017–19 period of stable economic conditions. The pandemic's impact on the economy and credit markets was significant, and the unprecedented policy responses in the form of lockdowns and monetary and fiscal policy were significant as well. Economic and financial forecasts deteriorated during this period.[12] CECL allowances increased significantly early in the pandemic, as a result of a combination of worsening economic forecasts, the added flexibility of the CECL framework, and more expansive provisioning requirements. CECL allowances reached their peak in 2020:Q2, while allowances for

[11] Data publicly available at www.chicagofed.org/banking/financial-institution-reports/bhc-data. Our sample comprises BHCs with more than $5 billion in consumer loans as of the end of 2019, in order to increase homogeneity. A small number of institutions that reported CECL allowances for the first time at some point after the first quarter of 2020 are also excluded. Loudis et al. (2021) and Rosenblum and Lai (2020) report information similar to figure 1.

[12] Unemployment rose in the U.S. in April 2020 to 14.7 percent from a reported 4.4 percent in the prior month, and then it decreased rapidly over the remainder of the year at about 1 percentage point per month in the first few months, reaching a rate below 4 percent by the end of 2021. Pinello and Puschaver (2020) provide a financial account of the challenges faced by CECL adopters in the first quarter of 2020. Wall (2020) addresses regulatory efforts to minimize the impact of CECL in the early days of the pandemic.

nonadopters reached their peak in 2020:Q3. Allowances decreased significantly during 2021, as economic conditions improved, and remained relatively stable in 2022.[13] Figures 2.b to 2.d depict the behavior of allowances for CECL adopters and nonadopters across consumer loan portfolios: residential, credit cards, and autos. While both adopters and nonadopters responded to the pandemic by increasing allowances, CECL adopters increased allowances by a much larger margin across portfolios, and at a faster pace, while charge-off rates decreased with respect to the already record-low levels of recent years.[14] Research by Bonaldi et al. (2023) documents greater accounting noise and reporting bias for CECL adopters. In subsequent sections, we delve into a more detailed analysis of the challenges faced by financial institutions as reported in public financial disclosures.

C. Research on CECL Adoption

The adoption of CECL has generated extensive academic and policy research around the implementation and impact of the novel allowance methodology. Some research highlights the potential advantages of a forward-looking allowance framework for risk management and financial disclosures. Other research highlights challenges of the new framework, which include the procyclicality of allowances and the reliance on economic forecasts, which may increase the volatility of bank earnings and reduce lending. Other concerns include the impact of CECL adoption on banks and regulators incentives. Additional practical concerns relate to the complexity of the CECL framework and implementation burdens.[15] Our research fills a gap in the existing literature by analyzing the sensitivity of the CECL framework to forecast and model error. Research by Harris et al. (2018) develops a measure of one-year-ahead realized losses on banks' loans portfolios combining various measures of credit risk disclosed by banks. Their measure contains incremental information about one-year-ahead realized credit losses relative to the

[13] Beck and Beck (2022) report the same performance of provisions across CECL adopters and nonadopters and suggest that this represents preliminary evidence that ASU 2016–13 has achieved its objective of making allowances more sensitives to changing economic conditions. Chen, Dou, Ryan, and Zou (2022) argue that the observation that CECL adopters in 2020 increased provisions more than nonadopters is consistent with the CECL approach increasing cyclicality.

[14] FRED, St. Louis Fed (stlouisfed.org).

[15] For the less complex financial institutions, regulators have attempted to address some of these practical concerns with concrete, and simple, methodological frameworks, as we discuss in an appendix.

allowance for loan losses and analyst provision forecasts. Their work underscores limitations of an incurred loss framework that doesn't reflect all expected losses anticipated at the loan's inception. In related work, Lu and Nikolaev (2022) develop an empirical model of the present value of future expected losses on existing loans, conditional on forward-looking information. Their estimated allowance for expected losses is a more effective predictor of medium-run losses than the incurred loss framework. The authors stress the importance of timely provisioning and the widely held view that lack of timely provisioning can be detrimental to the stability of the financial sector. Consistent with Bushman and Williams (2015) the authors also find support for the assumption that greater bank loss overhang is linked to higher future market risk exposure, for a given expected loss level.

Recent theoretical work by Mahieux, Sapra, and Zhang (2023), analyzes the complex interaction between the allowance for loan loss and the incentives of banks and regulators. The paper highlights the potential ambiguous impact of the implementation of a novel framework of provisioning for expected losses. Their analysis suggests that timely loan provisioning for expected losses can enhance a bank's incentives to originate safer loans and can improve financial stability, contingent on effective regulatory intervention. However, banks may end up taking excessive risk and financial stability may be negatively impacted when regulatory interventions are not very effective. Thus, it is important to empirically analyze the performance of the novel allowance framework under a variety of economic conditions.

The non-prescriptive nature of CECL affords significant flexibility in how ALLL is computed; it can also add transparency to financial statements through enhanced disclosures. Research by Gee et al. (2025) indicates that CECL adoption improves banks' recognition of loan deterioration and changing economic conditions and enhances forward-looking and quantitative information in investor disclosures. The study didn't observe a significant shift in risk appetite or credit supply. Research by Hu (2024) reports a reduction in small business loan originations in counties far from banks physical branches and hypothesizes that this may be due to higher information acquisition costs associated with CECL adoption. Loudis et al. (2021) find no significant evidence of a direct impact of CECL on lending during the COVID-19 crisis, although this particular downturn was unusual because of its level of government support to consumers and businesses, and because banking regulations were temporarily adjusted to accommodate concerns about CECL's implementation (Wall 2020).

Research by Loudis and Ranish (2019) indicates that CECL is likely to exhibit cyclicality, which will be conditional on the level of forecasting accuracy in anticipation of a downturn. Specifically, under perfect foresight of economic conditions, financial institutions will be able to adjust their CECL allowances in anticipation of a downturn. A myopic forecast, by contrast, will necessitate a significant increase in allowances over the unanticipated downturn. Alternatively, a low-foresight scenario will result in a level of allowance adjustment somewhat in between the perfect foresight and the myopic case.[16] The CECL framework recognizes expected future losses beyond incurred losses, in contrast with the incurred-loss framework. Because of this, there was broad agreement among studies on the assertion that if CECL had been adopted before 2007, the banking industry would have accumulated higher reserves in the early days of the Great Recession. There is also broad agreement that peak levels of allowances during downturns are higher under CECL, as the allowance in that case is determined over the life of the loan. [17] These views are also broadly consistent with the experience of CECL adopters in the U.S. during the recent COVID-19-induced economic downturn.

III. CECL Forecasting Pitfalls

Financial institutions faced significant challenges incorporating the impact of COVID-19 into CECL projections. To manage these challenges, firms relied heavily on overlays and other judgment-based adjustments to their model projections. A reliance on model adjustments points to weaknesses in the allowance framework in times of stress, when confidence in the framework matters most. It also underscores the importance of drawing lessons from crisis episodes in order to improve the robustness of the allowance framework in anticipation of future crisis.

[16] A BIS paper (2021; WP-39) conducted a literature review and noted the difficulty in identifying the causal feedback of a new allowance standard due to interactions between regulations, economic policy, and data limitations.

[17] Covas and Nelson (2018), DeRitis and Zandi (2018), Loudis and Ranish (2019), and Chae, Sarama, Vojtech, and Wang (2018).

Model accuracy is an important objective; one cannot always aim for projections that are conservatively inaccurate in periods of stress when the underlying framework has significant shortcomings. In addition, model accuracy impacts a second objective of CECL, which is balance sheet transparency.[18] It is important to recognize the roots of the bias in order to address model shortcomings and to implement model infrastructures that are resilient to shocks and are less reliant on adjustments and overlays.

The CECL reliance on reasonable and supportable forecasts inherently increases the sensitivity of the allowance to economic forecasting errors, particularly during periods of economic stress when forecasting accuracy is diminished. A less frequently discussed source of bias can arise as a result of model misspecification. Intuitively, model misspecification occurs when a model is a poor representation of the process that it intends to mimic. Model misspecification error is a biproduct of the unique challenges that a new crisis usually brings. It differs from error in economic forecasts in that it applies to the core models within the allowance framework and can result in biased predictions even in cases when economic forecasts are accurate.[19]

Next, we discuss model risk challenges faced by financial institutions during COVID-19 and mitigating strategies that were implemented. We then formally analyze the challenges of economic forecast and model misspecification error. Finally, we consider potential strategies to palliate the impact of economic forecasting and model misspecification errors in CECL projections.[20]

A. Firms' Adjustments to CECL Projections in the Time of COVID-19

Credit risk models were clearly impaired by the macroeconomic effects of the pandemic and the associated government response, including lockdowns and assistance programs. A recent BIS (2022) newsletter offers an international perspective into the strategies leveraged by

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[18] Pinello and Puschaver (2022) provide a financial account of the challenges of implementing CECL during the pandemic, including an overreliance on management's judgment in view of the challenges interpreting results from CECL models.

[19] A popular quote among statisticians is that "all models are wrong, but some are useful."

[20] In a recent speech, Federal Reserve Governor Christopher J. Waller (2021) stressed the limitations of economic forecasting by highlighting that "forecasters need to approach this work with humility." He also emphasized that "economic forecasting is a pretty hopeless endeavor. So why do we do it? Because of how much is riding on the outcome."

financial institutions to mitigate model risk and adapt their credit risk modeling policies and practices to the challenges of the pandemic.[21] Banks applied sizeable judgment-based adjustments (overlays and overrides) to their provisioning models to account for the significant divergence from historical patterns and trends. This resulted in monitoring controls and governance challenges around model adjustments. First, challenges around controls regarding model risk management and data; second, challenges capturing economic uncertainty; and third, challenges identifying credit deterioration in vulnerable sectors and borrowers. Efforts to address these challenges included: (1) exclusion of COVID-19-related data, primarily owing to the observed disconnect between macroeconomic variables and default rates; (2) utilization of new data collected during the COVID-19 pandemic with the application of judgmental overlays to counteract any changes to existing relationships (e.g., macroeconomic variables versus defaults); (3) enhanced infrastructure and data feeds to ensure proper integration of novel data into analysis of decision-making systems.

The U.S. CECL implementation shares many similarities with the international (IFRS 9) experience, but it is sufficiently different to warrant additional inquiry. To that effect, we reviewed public annual bank reports for 2019–21 along with quarterly earnings call transcripts for 2019Q4–2020Q4 for a sample of 10 U.S. banks with assets above 100 billion and a significant consumer finance presence. These public disclosures point to significant challenges of CECL implementation and allowance projections. Historical data became less reliable when banks were faced with the unprecedented impact of the pandemic, leading to increased estimation and forecasting uncertainty. It was particularly challenging to incorporate the impact of government stimulus and relief programs that altered typical consumer behavior. Specifically, these programs boosted customer financial health and liquidity, leading to strong credit performance, lower delinquencies, and a reduction in credit risk more generally. The potential duration and magnitude of these programs was also a source of uncertainty for banks, as the severity of the crisis led to program extensions.[22] This level of uncertainty on models and forecasts necessitated

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[21] See the BIS (2022) newsletter on COVID-19-related credit risk issues (https://www.bis.org/publ/bcbs_nl26.htm).

[22] For example, student loan relief programs were extended multiple times, as highlighted in a Congressional Research Service program report (2024).

significant management judgment and the application of model overlays and qualitative adjustments.

Model risk as a result of uncertainty in model inputs, model misspecification, and implementation challenges was also highlighted as an area of heightened concern during COVID-19. Banks had to conjecture the impact of government actions on key economic variables driving their model projections. Equally challenging was to conjecture the impact of debt relief programs on credit risk, both while the programs were active and after their conclusion. While the programs provided immediate relief, they also introduced uncertainty into the forward-looking models used for CECL. Banks recognized the effect of government programs in reducing delinquencies but expressed caution about the programs' potential temporary nature and the possibility that they were merely delaying, rather than preventing, losses. Traditional historical data and historically stablished patterns and relations between model inputs and outputs became less reliable and less predictive in this unprecedented environment. Banks generally adopted a cautious approach, often not fully incorporating the benefits of ongoing or potential future stimulus into their reserves, acknowledging the potential for delayed losses once the assistance ended. Ultimately, government assistance programs likely resulted in a greater reduction in credit losses than initially expected.

Another challenging aspect of the pandemic was an economic environment that fell outside the historical range experienced in the model training data (Altig et al., 2020). This at times necessitated adjustments to model methodologies and assumptions. Rapid shifts in emerging trends, the economic environment, and borrower behavior increased the need for timely information, while data volatility and uncertainty created challenges of measurement errors and inaccuracies in model inputs. Different segments of consumers and different types of credit posed unique challenges, i.e., prime versus subprime consumers, or secured versus unsecured, and installment versus revolving credit, requiring a granular assessment of credit risk.

B. Errors in Economic Forecast and Model Misspecification

Errors in economic forecast present significant challenges to CECL projections. CECL allowances constitute forward-looking estimates of credit losses, with reasonable and supportable forecasts representing a critical input in its calculation. The impact of economic forecasting error was substantial during the COVID-19 pandemic.[23] To illustrate the potential magnitude of forecasting error, we review the historical evidence on one-year-ahead forecast accuracy from the Philadelphia Fed's *Survey of Professional Forecasters* (*SPF*). For simplicity, we focus on the forecast of the unemployment rate, which is an important macroeconomic driver of CECL projections across consumer finance portfolios. Figure displays the unemployment rate for the period 1970–2022; the figure also displays the level of the one-year-ahead average forecasting error from the *SPF*. Before the COVID-19 pandemic, the largest one-year-ahead forecasting error was 4 percent in absolute value, which was achieved during the Great Recession. In contrast, during the initial days of the pandemic, partly as a result of lockdown mandates, the unemployment rate increased suddenly to above 14 percent, and the one-year-ahead forecasting error increased to a record 9 percent in absolute value.

CECL offers the flexibility to increase allowances in anticipation of economic downturn conditions, but this requires some level of forecasting accuracy. Based on the experience from the two most recent crisis episodes, we can expect economic forecast uncertainty to increase significantly during periods of stress and CECL projections to be significantly impacted. The effect of economic forecasting errors on allowances is unlikely to be homogeneous. It will vary across portfolios and across risk segments of a portfolio. It will also vary across model specifications.

Model misspecification error also presents significant challenges to CECL projections. To analyze these challenges, we begin with a simple statistical representation of the problem of generating forward-looking estimates k periods into the future of a certain quantity of interest y,

$$y_k = \psi_k(s, m_k) + \in_k,$$

where y_k represents the value of y k periods into the future, which is a function of portfolio characteristics s, reasonable and supportable forecasts of economic conditions up to k periods

[23] For example, Canals-Cerdá (2020), looking at credit card portfolios, observed that the impact of forecasting error could have been substantial during the initial quarters of the Great Recession, with deviations from the baseline between 30 percent and 40 percent in most segments.

into the future, denoted m_k, and a residual stochastic unpredictable component $\in_k$, which accounts for additional unexplained variability in outcomes. In practice, a forecast $\hat{y}_k$ requires forecasts $\widehat{m}_k$ of macroeconomic conditions and unbiased estimates $\widehat{\psi}_k$ of fundamental relationships. In some cases, it may also require estimates of certain aspects of the distribution of $\in_k$. The projection can then be computed as, $\hat{y}_k = \widehat{\psi}_k(s, \widehat{m}_k)$.

We adopt the terminology of Hendry and Mizon (2014) in order to better understand and illustrate modeling challenges.[24] These authors categorize the problem of unpredictability in econometric modeling and forecasting into three distinct types, each with different implications. Informally, these three categories can be described as: (1) anticipated stochastic variation in forecasts, (2) unexpected instances of outliers, more commonly known as "black swans," and (3) unanticipated shifts in the relevant relationships postulated by the model, also known as "regime shifts" in certain contexts. More formally, the authors define these categories as: (1) intrinsic unpredictability, (2) instance unpredictability, and (3) extrinsic unpredictability, respectively. This categorization offers a useful tool to better understand modeling challenges across different economic environments and for formulating strategies to minimize their impact.

Intrinsic unpredictability is the result of innate uncertainty in forecasts; thus, it is inherently unavoidable. The second and third categories are conceptually different but may be difficult to distinguish in practice. The case of *instance unpredictability* can be described by a probabilistic process subject to a nonnegligible probability of a nonpersistent unexpected "black swan" event. This case can be explained within the framework of the postulated probabilistic process, perhaps as a result of fat tails in the distribution of the model residual. By contrast, the case of *extrinsic unpredictability* refers to a persistent distributional shift that cannot be reasonably explained within the framework of the postulated probabilistic process. After a distributional shift, outliers may become a common occurrence. A persistent change in economic relationships for an extended period of time would fall into the category of *extrinsic unpredictability*. Intuitively, this may be the primary differentiating feature between categories two and three.

[24] Zhang, Harvineet, Marzyeh and Shalmali (2023)) analyze the problem of model performance from the perspective of the machine learning literature. Breeden (2018) presents an early study of the impact of model specification assumptions on the cyclicality of CECL projections prior to CECL implementation and prior to the pandemic.

The two most recent crises, the Great Recession and the pandemic, are arguably examples of *extrinsic unpredictability*. In the case of the Great Recession, mortgage defaults increased considerably while home prices experienced unprecedented drops.[25] Lenders' recoveries from defaulted mortgages also decreased markedly as a combination of lower home prices and increased time to foreclosure and sale. This level of stress in the mortgage market persisted for several years and was significantly different from prior experience.[26] In the case of the pandemic, life as we knew it changed suddenly and dramatically, as did important economic variables, like unemployment. The impact of the pandemic and the resulting government policies had a long-lasting impact on borrower behaviors.

The pandemic triggered unprecedented levels of government intervention, which included direct assistance to households, extensions of unemployment benefits, as well as programs directly targeted at consumer lending. It is not surprising that significant government interventions, unaccounted for in models during the pandemic, could lead to significant bias in model projections. The unprecedented level of government assistance impacted the future credit performance of banks' loan portfolios and contributed to a breakdown in the traditional relationships between economic variables and measures of credit risk, and portfolio loss, for a prolonged period. We can generalize our simple statistical framework by incorporating the effect of government assistance as in the following expression,

$$y_k = \Phi_k(s, m_k, g_k) + \in_k,$$

where g_k represents government assistance programs that were introduced at different points during the pandemic and were omitted from pre-pandemic models, as they were absent from the historical data.

Government assistance during COVID-19 included multiple novel complex programs directed at consumers that evolved over time with the severity of the crisis, as well as the TALF program directed at maintaining liquidity in consumer finance markets and the availability of

[25] fred.stlouisfed.org/series/csushpinsa
[26] fred.stlouisfed.org/series/DRSFRMACBS

consumer credit. As a result, the equation postulated above cannot generally be directly estimated, given the lack of historical data along with other identification and endogeneity challenges. However, it can still be informative about sources of model misspecification, along with potential strategies to mitigate bias in projections. Model misspecification error can lead to biased projections, even in the case of accurate economic forecasts. In our case, the relationship Φ_k may differ substantially from the estimated relationship ψ_k before the pandemic. Thus, the typical sources of model misspecification, functional form misspecification and omitted variables, are represented in the above equation. Predictions $\hat{y}_k$ relying on precrisis estimates of $\hat{\psi}_k$ will likely lead to systematic forecast bias, consistent with the case of extrinsic unpredictability, unless model misspecification bias is acknowledged and properly addressed. Models trained with historical data over the period of the Great Recession were poorly equipped to forecast the impact of the pandemic as well as the effects of fiscal and monetary policy actions. The level of government support significantly minimized the severity of economic outcomes.[27] Therefore, it is perhaps not surprising to observe a disconnect between allowances and charge-offs, as depicted in Figure 1.[28]

C. Mitigating the Impact of Forecasting Error and Model Misspecification

Error in macroeconomic forecasts and a more fundamental problem of model misspecification are potential sources of CECL bias, as discussed above. Macroeconomic forecasts are inherently uncertain, and the level of uncertainty generally increases in challenging economic environments, like the early stages of a financial crisis or a pandemic. Thus, lessons learned from prior crises suggest that reasonable and supportable forecast horizons are likely to be shorter in periods of high uncertainty. It may also be helpful to translate uncertainty in forecasts into CECL projections, for example, by considering multiple scenarios with the importance assigned to different scenarios commensurate with the level of confidence. During periods of elevated

[27] International accounting standard setters have emphasized that banks should consider the impact of government policies in their analysis of allowances (De Araujo, Cohen, and Pogliani 2021). The results in Degryse and Huylebroek (2023) are consistent with a positive impact of government fiscal policy on banks' credit risk and profitability.

[28] The experience of the Great Recession also generated significant debate about model performance during crisis periods (see, for example, Gerardi, Lehnert, Sherlund, and Willen (2008) and Frame, Gerardi and Willen (2015)).

economic uncertainty, it may also be helpful to look for novel sources of information and external benchmarks, as well as to consider more frequent model development, outcome analysis, and validation of forecasts.

How can we mitigate CECL sensitivity to model error under extrinsic unpredictability conditions? Extrinsic unpredictability conditions can lead to long-lasting changes in model-postulated relationships. Thus, in these instances, it may be necessary to adapt and modify models to the realities of a novel environment in order to be able to overcome ingrained misspecification bias. The models and strategies to be considered in periods of uncharted economic conditions can be informed by insights from econometric theory, by an analysis of primary and auxiliary data after the shock, as well as by expert judgment.[29]

Hendry and Mizon (2014) point out that it may be possible to address the effects of extrinsic unpredictability ex post. Novel evidence available after a shock can inform model selection and re-estimation, and sources of misspecification and forecast failure can be potentially addressed.[30] 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. Thus, simple economic reasoning and expert judgment can help us address model shortcomings and identify model specifications that are more suitable to the novel environment. Simple model specifications that use robust sources of information and are less reliant on potentially biased information may prove 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 enhance the information set after the shock and serve as an early warning of model performance bias. It may also be possible to leverage the information of early indicators to ascertain the performance of standard measures of portfolio risk and to discriminate across model candidates. Overreliance on a single model is likely 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 argue in the empirical section of the

[29] Model misspecification during a crisis is only one possible source of forecasting bias. For example, measurement error in input variables broadly defined could be considered as another candidate for further analysis.

[30] A recent speech by Fed Governor Waller offered advice for tackling challenges, beyond forecasting errors, that often arise during periods of economic stress arising from unprecedented circumstances. Waller advised that "when the shock is unique, adapt fast." This requires careful analysis of the novel shocks and may also require modifying and adapting models to the novel environment.

paper. Thus, it may be useful to regularly evaluate the strengths and weaknesses of different model specifications.

IV. An Application to Consumer Finance Portfolios

In the previous section, we highlighted the advantages of a flexible and adaptable modeling framework that can quickly adapt to the challenges of a novel crisis. In this section, we advance our views by presenting an econometric framework that is nimble and adaptable and consistent with the typical modeling framework implemented by the most sophisticated CECL adopters. We also leverage this framework to analyze the usefulness of some of the strategies previously discussed to palliate the impact of model misspecification error.

The modeling framework considered can be estimated and deployed quickly, irrespective of the size of the portfolio considered. For this reason, the approach is particularly valuable in consumer finance, in which the typical loan portfolio comprises many millions of loans, like personal loans, mortgages, auto loans, or credit card loans. Mortgages and credit cards have received significant attention in the literature, especially regarding their performance during the Great Recession. We consider an application for auto loans, which have not previously received the same level of attention.

A. The Data and the Auto Loan Market

Auto lending is a key contributor to consumer finance and the overall economy. Mortgages, auto loans, and credit card lending are the most important segments of consumer finance in banking. The auto loan market, at $1.66 trillion at the end of 2024, represents the second-largest segment of consumer finance by outstanding balances. By comparison, credit cards represent close to $1.21 trillion and mortgages about $12.61 trillion in outstanding balances.[31] About 60 percent of

[31] In addition, student loans represent about $1.62 trillion, but about 90 percent are government guaranteed.

U.S.[32] adults with a credit report have an auto loan; this number is about 40 percent larger than the number of mortgages.

The three main providers of auto loans in the U.S. are banks, credit unions, and finance companies. The size of the auto loan market and its prevalence across different types of lenders highlights the significance of conducting research on CECL for this lending category. Furthermore, auto loans are secured closed-end loans, i.e., the loan terms typically involve specified monthly payments over a fixed period, and the car represents the loan collateral. Auto loans share many similarities with popular fixed-term mortgage loans and other types of closed-end consumer finance loans. Thus, our analysis applies more broadly to a larger class of consumer finance loans.

Auto lending data reported to credit bureaus is broadly representative of the overall auto lending market, with the vast majority of auto lenders reporting, although it may not be representative of a small percentage of loans originated by car dealerships or sales financing. In this study, we leverage historical information from Equifax, one of the three primary U.S. credit bureaus. Specifically, we employ data from the FRBNY Consumer Credit Panel/Equifax (CCP), and in particular its associated auto tradeline panel data. The CCP is a panel data set comprising information from anonymized individual credit bureau reports starting with the first quarter of 1999. The panel comprises a nationally representative 5 percent random sample of individuals with a credit history.[33] The auto tradeline panel associated with the CCP was constructed to provide additional loan-specific information on associated auto loans. The CCP auto tradeline includes snapshots of the auto tradelines in the credit bureau data at periodic intervals. It includes loan-specific origination information such as origination date and loan balance, and monthly performance information. Tradeline information can be complemented with additional borrower-specific credit bureau information available in the main CCP panel, like the borrower Equifax Risk Score (Risk Score).

While the tradeline data provides valuable information about the performance of auto loans, it also has some limitations for the analysis of allowances. Specifically, tradeline data does not include information on recovery values in the case of default — information that is readily

[32] 2024Q4 FRBNY Consumer Credit Panel/Equifax.

[33] Lee & Van der Klaauw (2010) describes the data in more detail, Grunewald et al. (2020) and Canals-Cerdá and Lee (2024) provide additional institutional details about the auto lending market.

available to lenders. For this reason, our empirical framework will focus on the analysis of default rather than the analysis of loss. We also restrict our sample to loans issued by banks and credit unions in order to focus our analysis on depository financial institutions. We complement the auto tradeline data with additional information on key macroeconomic variables, primarily state unemployment.[34]

Banks and credit unions have generally a higher concentration of safer loans when compared with the overall market, with nonbank lenders having a larger concentration of subprime borrowers. **Figure** depicts changes over time in early delinquency for our representative portfolio. The figure highlights the significant increase in default risk over the period 2008–11, around the time of the Great Recession. In contrast, delinquency generally decreased during the pandemic, particularly severe delinquency.

Intuitively, a model's forecasting ability is in good part determined by the information embedded in the historical training data. With this in mind, in figure 5, we parse out the variation in unemployment rates across states, which is the primary source of macroeconomic variation informing our models. The figure provides information that will help us understand the performance of models with different sets of training data. Most of the variation in the unemployment rate from 2001 to 2007 is concentrated in unemployment rates between 3 percent and 7 percent. This contrasts with the 2009–11 period, during which unemployment increased significantly across the board, with unemployment rates concentrated between 6 percent and 12 percent. The experience in 2020 was even more remarkable. Suffice it to say that the year started with an aggregated unemployment rate of 3.5 percent that jumped to 14.7 percent in April of that year, at the onset of the pandemic. Unemployment across states in the first half of 2020 was concentrated within the range of 2.2 percent to 28.5 percent, with the largest value achieved in April in Nevada, a state that was severely impacted by lockdown mandates.

B. The Empirical Framework

[34] Data source Bureau of Labor Statistics.

Consider a loan portfolio that can be divided into S segments of loans with broadly homogeneous risk characteristics. Each segment is composed of loans with the same, a priori, independent probability of default p. It follows then that the aggregated default distribution for a segment of N loans will follow a binomial distribution $B(N, p)$. Furthermore, for an N large enough, the Poisson distribution *Poisson(λ)*, with λ=Np, represents an excellent approximation to the $B(N, p)$ distribution. Thus, our empirical strategy considers the estimation of segment-level Poisson models for the number of defaults n_{sl} in each period ahead of the postulated life of the loan $l = 1, \dots, L$, for each segment S of N_s loans for each vintage in our estimation data set. Specifically, we postulate that the number of defaults n_{sl} associated with segment S in period l can be represented by the Poisson distribution,

$$n_{sl} \sim P(\lambda_{sl}, N_l) \text{ for } s = 1, \dots, S \text{ and } l = 1, \dots, L$$

In our empirical specification, we consider a standard parametrization $\lambda_{sl} = \lambda_l(X_s, m)$, with X_s representing segment specific characteristics and m representing region-period specific macroeconomic drivers. We also consider a more flexible, segment-specific parametrization, which is ultimately our specification of choice.

The impact of economic conditions on the risk profile of a portfolio of consumer loans is typically identified by the historical variation in economic variables over time and across geographic regions, most often across states. With loan level data representing T snapshots, or cohorts, of a loan portfolio and credit performance up to L periods ahead, we can leverage the heterogeneity in macroeconomic conditions and performance across regions and over time. Loan-level data can be aggregated at the segment-geography level as

$$\left\{(N_{sgt}, n_{sgtl}, m_{sgtl}): s = 1, \dots S;\ g = 1, \dots, G;\ t = 1, \dots, T; l = 1, \dots, L\right\},$$

with N_{sgt} representing the number of loans in a specific segment-geography for a particular snapshot t, n_{sgtl} representing the number of associated defaults in performance period l, and m_{sgtl} representing macroeconomic conditions in geographic unit g at period l.

With modern statistical software, after data manipulation, the approach can be implemented with a single line of code; for example, by using the General Structural Equation Modeling (GSEM) available in Stata.[35] In our preferred model specification, we consider a segment-specific parametrization of λ_{sl}, with unemployment and the six-month unemployment change as macroeconomic risk drivers. The approach can be applied to the estimation of unconditional (our preferred method) or conditional probabilities. The estimation of unconditional probabilities is often more robust because the conditional probability framework can be impacted by potential propagation of model forecasting error. Using the estimated Poisson framework, along with macroeconomic projections $\widehat{m}_{sgtl}$, we can derive forecasts of segment defaults $\hat{n}_{sgtl}(\widehat{m}_{sgtl})$ or segment default rates $\hat{n}_{sgtl}(\widehat{m}_{sgtl})/N_{sgt}$.

Importantly, note that the size of the resulting data set, after the segmentation scheme has been determined, is a function of S, the number of segments, rather than a function of the portfolio loan sample size. Thus, the sample size of the original portfolio becomes muted. This is particularly important for consumer loan portfolios of mortgages, autos, and credit cards, with potentially tens of millions of loans, or even hundreds of millions of loans in the case of credit cards. As a result, we can conduct the empirical analysis on a portfolio of any size without increasing the computational burden. Specifically, in our empirical example, we employ the whole sample of auto loans in the consumer credit panel from 2001 to 2022, consisting of all auto loans originated in the United States by the nationally representative 5 percent random sample of individuals with a credit history that make up the panel. Our models can be estimated and deployed in minutes.

C. Selection of Segmentation Scheme

One potential problem with the approach described in the previous subsection is that it becomes impractical when the number of segments is large enough. The approach can incorporate

[35] See Canals-Cerdá (2022) for a description of the GSEM framework and an illustration of this powerful framework.

continuous variables as long as they are constant within segments but not necessarily constant over time. This is typically the case for macro variables, which are constant at a certain aggregated geographic level — the state in our case. However, other continuous variables will have to be incorporated into a segmentation scheme in order to be included in the empirical framework. In order to select an optimal segmentation scheme, we employ a ML classification algorithm on a 20 percent random sample of the data across all vintages during 2001–20, with the target variable defined as the two-year forward default, which takes the value one if the loan defaults within two years and zero otherwise, and with features including Risk Score and loan size at origination.[36] Note that the segmentation scheme implicitly incorporates multiple risk dimensions, as the typical Risk Score leverages information on credit, debt and payment history, credit mix, credit access or ability to borrow, and credit inquiries, among others.

Other segmentation options include an expert judgement segmentation based on business needs or a segmentation inspired by regulatory requirements. For example, the Federal Reserve FR Y-14Q Auto submission requires banks to report portfolio information at the segment level by product type, age, original LTV, credit score, delinquency, and geography, resulting in a segmentation scheme with a few thousand segments. Even in the case of non-statistical-based segmentation schemes, statistical-based information will most likely contribute to the segmentation. In the example of the FR Y-14Q Auto submission, the credit score in particular represents an important element of the segmentation scheme. As an additional example, financial institutions may select segmentation schemes based on the loan origination channel (branch, online, auto dealer, etc.) as a complement to statistical-based segmentation. This additional layer of segmentation may be justified based on business needs. We focus our attention on segmentation purely based on statistical principles.

Figure 6 reports receiver operating characteristic (ROC) metrics from our ML segmentation approach applied across vintages. We evaluate the performance of multiple segmentations with an increasing number of segments. Consistent with industry practice, we evaluate performance with training/test samples from our original data. Specifically, training data is employed for

[36] We employ a classifier technique within the scikit-learn ML library based on the entropy criterion (ref. sklearn.tree.DecisionTreeClassifier — scikit-learn 1.2.1 documentation).

statistical model development, while testing data is not part of the development process and is used to assess the discriminatory power of multiple segmentation schemes outside the training environment. Figure 6.a graphically depicts the ROC performance as the maximum depth of the tree increases from one to 23. While the ROC performance continues to increase with the maximum depth in the training data, using the test data instead, we observe that the ROC does not significantly increase after a maximum debt of three. Therefore, for our empirical application, we select an optimal segmentation scheme based on a maximum depth of three, resulting in a segmentation scheme with eight segments.

In order to analyze the stability of the segmentation scheme over time, we consider the ROC performance of the segmentation scheme across year cohorts, from 2001 to 2020. This information is reported in Figure 6.b. As the figure indicates, the ROC of the segmentation scheme remains stable over time, taking values that range from 0.81 to 0.84. Perhaps not surprisingly, the ROC metric deteriorated slightly in crisis environments and recorded its lowest values in 2006–09 and 2020, i.e., around times of significant economic uncertainty.

V. Empirical Findings and Lessons Learned

Our focus in this empirical exercise will be on the problem of model misspecification error, which has received less attention from practitioners than the problem of macroeconomic forecasting error. Model misspecification errors have usually been addressed by practitioners with model overlays and overrides, relying primarily on expert judgment and auxiliary information, without directly tackling the roots of the problem. Here, we leverage our simple empirical framework to examine the effects of model misspecification error in times of high economic uncertainty and analyze strategies to mitigate its impact. We take advantage of our rich historical data, which encompasses two periods of significant economic uncertainty, the Great Recession and the pandemic. The next two subsections analyze model performance and limitations specific to each crisis period. Lessons learned during past crisis episodes can provide useful guidance for addressing challenges that banks may encounter in future crisis. A third subsection summarizes lessons learned and takeaways in the context of model and forecast challenges that banks faced during CECL implementation amid the pandemic.

A. Model Performance During the Great Recession

In order to focus on the impact of model misspecification bias, we assume perfect macroeconomic foresight and a nine-quarter reasonable and supportable forecast period. Figure 7 presents realized and forecast nine-quarter default rates for cohorts of newly originated auto loans from the 2001 to 2014 cohorts. The figure illustrates the impact of different training data sets on the out-of-sample performance of model projections. The solid line depicts the realized nine-quarter forward default rate, while all other lines represent model projections using our preferred model specification estimated with different training data sets, including the 2001–05, 2001–07, 2001–08, and 2001–09 cohorts. The model estimated with data from the 2001–05 cohorts perform well in times of benign economic conditions, before and after the period of the Great Recession, but it performs poorly during the period of the Great Recession, characterized by significantly higher defaults. In order to understand this performance, note that the 2001–05 cohorts experienced mostly benign economic conditions, characterized by relatively low levels of unemployment during the first nine quarters after origination, as illustrated in figure 5. A model estimated using the 2001–07 cohorts performs much better during the period of the Great Recession. Considering data from the 2001–08 cohorts further improves model fit during the period of the Great Recession; adding additional cohorts does not improve performance significantly.

It may also be helpful to analyze model performance across segments. Looking at figure 8, we observe that the performance of models across risk segments follows a similar pattern as the performance at the aggregate level. However, for the riskiest segments, the default rate seems to deteriorate more rapidly in the early stages of the Great Recession.

Finally, while the focus until now has been on model performance over a nine-quarter period, we may be able to draw additional insights from looking at the lifetime allowance performance prescribed in CECL. For the purpose of our analysis, we assume a life of a loan of five years, with a nine-quarter period of reasonable and supportable forecast. Figure 9 reports realized lifetime defaults across cohorts and modeled CECL lifetime estimates of default. The estimated lifetime default rates combine a nine-quarter estimate of default under perfect foresight of economic conditions, with a remaining-life-of-the-loan estimate of default beyond nine quarters that represents an over-the-cycle estimate over a mix of economic conditions. We observe that the model-projected lifetime default rate generally lies above the realized default rate in periods of good economic conditions, while it lies below the realized default rate during the period of the Great Recession. What explains the performance of CECL projections? On the one hand, defaults during the Great Recession remained elevated beyond the assumed nine quarters of perfect macroeconomic foresight; this explains the CECL underprediction during the Great Recession. On the other hand, the long-run average default rate estimated with the 2001–07 cohorts includes the period of the Great Recession, resulting in estimates that are overly conservative during periods of benign economic conditions. Thus, lifetime CECL projections average out good and bad economic environments beyond the reasonable and supportable timeframe, and this explains the observed differences between realized and projected lifetime default rates.

B. Model Performance During the Pandemic

The COVID-19 pandemic generated significant stress among retail borrowers. It also triggered unprecedented levels of government assistance, including forbearance programs directly targeted at consumer lending. We have argued in this paper that this unprecedented level of government assistance contributed to a breakdown in the traditional relationship between economic variables and consumer credit risk, which prompted the divergence between historical charge-offs and allowances reported in figure 1.

Figure 10 looks at the evidence of model performance during the pandemic in our empirical application to auto loans. The figure compares nine-quarter realized default rates across cohorts, with projected default rates across different model specifications under perfect economic foresight. The solid line represents the realized nine-quarter default rate across cohorts; the dotted line represents projected nine-quarter default rate for a model estimated using our preferred model specification and data from the 2001–17 cohorts. The model provides a reasonable fit of the data up to the 2018 cohort. In contrast, model projections deviate significantly from realized outcomes for cohorts with a nine-quarter projection period overlapping with the period of the COVID-19 pandemic. Model projections fitted with data prior to the pandemic, forecasts dramatic increases in defaults consistent with the macroeconomic experience in the early days of the pandemic. However, the dramatic increase in defaults projected by the model never materialized.

Figure 10 also depicts projected defaults from a model estimated using our preferred specification and data from the 2001–20 cohorts (long-dashed line), which includes the period of COVID-19 pandemic. We also report projections from a model estimated with data from the 2001–17 cohorts but for a model specification that does not include macroeconomic drivers (dashed line). Thus, changes in projected default rates for this last model are driven only by cohort-specific risk characteristics. Observe that the default rate projections from these two models are almost the same. This is consistent with our intuition that model forecast error during the pandemic resulted in good part from the misspecification of the impact of macroeconomic variables during that period. This misspecification is the result of generous government policies directed to mitigate the effects of lockdown policies. Thus, addressing this misspecification problem directly by leveraging insights from sound econometric theory principles improves model performance significantly.

Figure 11 expands on figure 10 by depicting model performance across cohorts and risk segments. Consistent with findings in the prior subsection, there is significant value in tracking the performance across segments. Specifically, we observe a significant divergence in model performance between high-risk and low-risk segments. For the highest-risk segments, we observe that realized default rates decreased most significantly with respect to the pre-pandemic trend. This suggests that government policies had the largest impact on these segments of consumers. In contrast, we observe the largest impact of model misspecification in the lowest-risk segments, with the model estimated using the economic experience before the pandemic (dotted line) experiencing the largest divergence from observed outcomes in these lower-risk segments, proportionally.

C. Lessons Learned and Takeaways

Our analysis of allowances and credit risk expanding two crisis episodes, and our review of banks' public disclosures around the time of CECL implementation, may provide useful insights when confronting future economic stress environments. In the next paragraphs, we first analyze lessons learned from our empirical analysis of auto lending regarding the allowance framework under out-of-range economic environments and government interventions. We then conduct an exercise of robustness of empirical insights by leveraging a simple econometric framework applied to credit card lending. This exercise indicates that the lessons learned from our analysis of auto portfolios leveraging loan level data are applicable to a wider range of consumer portfolios, model specifications, and data aggregation levels. Finally, we highlight challenges of model risk management and validation specific to financial institutions.

Out-of-range economic environment: The pandemic and the Great Recession exemplify economic environments out of the range with historical experience. Banks' public disclosures and the recent historical record highlight the challenges associated with the projection of allowances in economic stress environments. Our empirical analysis indicates that model sensitivity to economic factors can generate biased projections of expected credit loss in uncharted economic environments characterized by out-of-sample macroeconomic conditions. However, when models are re-estimated with additional data that includes some exposure to the novel macroeconomic environment, performance can improve significantly. Thus, in times of crisis, it can be particularly important to contrast the projections of models in production with the predictions from challenger models estimated with novel or alternative data, whenever possible. Furthermore, not all models are equally sensitive to changes in macroeconomic conditions. In certain cases, simple challenger or benchmark models, perhaps with sub-optimal in-sample performance, can be less sensitive to bias under unusual economic environments and can provide more sensible projections of credit loss. Our analysis also highlights the importance of tracking model performance across segments in periods of crisis, as model projections across the lowest-risk or highest-risk segments may serve as an early indicator of the impact of model misspecification error when compared with realized outcomes in the early days of a crisis. Finally, certain CECL design features may also mitigate projection bias to a degree. Specifically, CECL long-run projections average out economic cycles, although short-term economic conditions remain a key determinant of allowances, and the time horizon of reasonable and supportable forecasts may be shorter in times of crisis. In general, it is important to understand the weaknesses and limitations of models and to have remediation plans and tools in place to address instances of model underperformance. These insights may assist in building model infrastructures that are resilient and adaptable in anticipation of future crises.

Government interventions: Crisis periods are often accompanied by significant levels of government support. In the case of the Great Recession, it was accompanied by measures to increase liquidity in the financial system, along with capital assistance programs, as well as other measures to restore confidence in the financial sector.[37] One important facet that was unique to the pandemic was the unprecedented level of government assistance targeted specifically at the individual. This level of assistance resulted in a clear breakdown in the traditional relationship between economic variables and credit risk in consumer finance portfolios. Banks, in their public disclosures, highlight the importance of government assistance programs in improving the credit performance of loan portfolios; they also highlight the significant uncertainty around the size and duration of these programs, which evolved in tandem with the severity of the pandemic. Leveraging econometric theory insights from section 3, in our empirical analysis, we explore the performance of models excluding macroeconomic drivers, which are a significant source of model misspecification, and observe that out-of-sample projections from these models are much more in line with the performance of auto loan portfolios during the pandemic. In the next paragraphs, we leverage data on credit card lending and conduct a robustness check that supports these findings. Another insight from our empirical work relates to the tracking of performance across risk segments within a loan portfolio. Specifically, our analysis indicates that model performance deterioration across the highest-risk segments can serve as an early indicator of the effects of government policies. Thus, our theoretical and empirical analysis indicates that it can be beneficial to explore a range of model specifications, especially during periods of crisis,

[37] For information on government response, see https://ypfs.som.yale.edu/us-government-crisis-response.

and to leverage econometric theory insights to discern how specific crisis features influence different model outcomes.

Expanding our analysis beyond auto lending: To substantiate the robustness of empirical insights, we expand our analysis to credit card portfolios using highly aggregated public data and a simple econometric framework. We employ publicly aggregated quarterly charge-off information from credit card portfolios for the largest 100 banks from the years 2000 to 2024.[38] We construct simple linear econometric models to project one-year-ahead annual portfolio charge-off rates as a function of lag measures of portfolio performance and macroeconomic variables. On the one hand, we consider simple models that project annual charge-off rates based on up to two quarter lags in delinquency and charge-off rates. We also consider versions of these models augmented with unemployment rate and change in unemployment rate up to two quarter lags. Figure 12 presents one-year-ahead projections from our preferred model specifications without macro drivers and with macro drivers, along with realized annual charge-off rates. The model specification with macro drivers provides a somewhat better fit of the data during normal times and more quickly adjusts to worsening economic conditions during the Great Recession. However, during the COVID-19 pandemic, when government assistance programs significantly impacted consumer finance portfolio performance, the model without macro risk drivers yielded a much better fit to realized outcomes. In this case, the model's reliance on current and lagged portfolio performance renders it less susceptible to model misspecification under extreme macroeconomic conditions and government assistance policies.

Challenges in model validation and governance: A model infrastructure designed for adaptability, incorporating insights from past crises and allowing for varied specifications, can alleviate validation constraints during periods of instability. However, we should also acknowledge the challenges of this strategy, especially for the most complex financial institutions. Our review of banks' public disclosures highlights multiple challenges of the CECL quantification framework at the most complex financial institutions, from the complexity of the quantification framework to the reliance on uncertain economic forecast and the interplay between models, adjustments, and overlays, among others. A recent report (Kumar, Laurent,

[38] Data available at https://www.federalreserve.gov/releases/chargeoff/.

Rougeaux, and Tejada 2022) indicates that validation of Tier 1 models in the U.S. requires 12 weeks on average, while Tier 2 and 3 models require six and four weeks, respectively. Furthermore, validation resources get strained during periods of crisis. For these reasons, it is important to plan ahead and to consider every aspect of the model life cycle as part of the model development process.

VI. Conclusions

CECL represents a significant change in the way financial institutions compute their allowance for credit losses. The new framework focuses on lifetime expected loss rather than incurred loss, and it is expected to add transparency to financial statements. Leveraging information from public quarterly financial disclosures and earning calls from a sample of the largest financial institutions, we document challenges of implementation related to framework complexity, validation, and audit, as well as model risk concerns stemming from an increased reliance on models and forecasts. Using publicly available consolidated financial statements, we analyze the performance of the CECL and incurred loss allowance frameworks across financial institutions around the time of the COVID-19 pandemic. Consistent with contemporaneous research we observe that, when compared with nonadopters, CECL adopters increased allowances by a much larger margin across portfolios, and at a faster pace, while charge-off rates decreased with respect to the already record-low levels of the past few years.

The recent COVID-19 crisis underscored the sensitivity of the CECL allowances framework to macroeconomic forecast errors and model misspecification bias during crisis periods. We analyze conceptually and empirically these problems and provide practical insights for mitigating their impact. The focus of our empirical work is on the implementation of CECL to consumer finance portfolios, perhaps the most challenging area of CECL implementation, given their size and complexity. Specifically, we examine auto loans portfolios, which have received less attention in the consumer finance literature. Our empirical implementation combines machine learning techniques with standard statistical principles. The approach considered is simple without compromising performance, can easily accommodate multiple models, and allows for quick and simple model redevelopment, redesign, and deployment, irrespective of the size of the loan portfolio. The simplicity of the framework can also streamline the model validation process.

Our empirical analysis looks back at more than 20 years of data and evaluates model performance during the Great Recession as well as the COVID-19 pandemic. Both events share some similarities, but the COVID-19 response involved substantially more direct government support for individuals. We observe that models usually underperform when presented with uncharted economic environments characterized by out-of-sample macroeconomic conditions. However, when models are re-estimated with additional data that includes some exposure to the new macroeconomic environment performance can improve significantly. Econometric theory can offer insight into the sources of model underperformance. Specifically, macroeconomic risk drivers were a significant source of model misspecification error during the pandemic. As a result, models without macroeconomic risk drivers produced projections that better aligned with observed performance during the pandemic. A simple extension of our empirical work to credit cards leveraging highly aggregated delinquency and charge-off data and simple models adds robustness to our analysis. We also observe that certain portfolio risk segments can act as early warning of stress. Furthermore, CECL long-run projections by design average out economic cycles to a certain extent, although short-term economic conditions are a key determinant of CECL allowances.

The primary objective of our research is the analysis of the performance of models of expected credit loss under economic stress environments. However, it is important to highlight that severe economic environments and government interventions also have long-term implications for the accuracy and reliability of historical data and the future development of credit risk models. These are important research topics of significant regulatory and industry interest. Uncertainty in economic variable measurement and mismeasurement of crisis impact on credit risk outcomes under government intervention remain persistent challenges in the historical record. For example, significant mismeasurement of unemployment during COVID-19 has been reported by the Bureau of Labor Statistics.[39] Uncertainty around indicators of economic activity and bias in the measurement of realized and potential tail credit risk contribute to the challenges of incorporating pandemic data into the empirical analysis of projected credit loss going forward.[40]

Insights from our empirical exercise include avoiding overreliance on individual models, comparing projections of models in production with alternative model specification that may be more robust to certain forms of model misspecification in periods of crisis and, whenever possible, to consider models that incorporate data with some level of exposure to a novel environment. It should also be useful to focus on the resiliency and adaptability of models and model infrastructure in times of crisis, and to consider flexible forecasts and forecast horizons. Simple models, whenever possible, may compare favorably to more complex models. Simple models may be more robust and easier to diagnose than more complex models. They may also be useful as benchmarks, can provide guidance when overrides or overlays are applied to primary models, and can also help identify areas of weakness in more complex models. There is value in leveraging multiple models and understanding their strengths and weaknesses. There is also value in considering redevelopment or redesign of models in environments that challenge established economic relationships. It is also important to take into account that crisis periods are often accompanied by significant levels of government support, which may evolve in tandem with the severity of the pandemic. We argue that econometric theory insights can provide useful insights that may help alleviate problems of model misspecification as a result of government intervention, in particular misspecification around macroeconomic factors. Under this scenario, models that exclude econometric factors and rely on alternative drivers of credit risk may outperform more complex models. In summary, when building models and model infrastructures, it is important to consider resiliency and adaptability to new shocks.

While we argue in favor of a flexible model infrastructure, we also acknowledge the challenges that regulated institutions face, especially taking into account expectations about

[39] https://www.bls.gov/blog/2020/update-on-the-misclassification-that-affected-the-unemployment-rate.htm.

[40] The analysis of economic relationships subject to measurement error in the classical case of independent errors is better understood than the non-classical case of errors correlated with the underlying true variable, which is significantly more challenging. Measurement error linked to severe economic environments and government actions naturally falls into the realm of non-classical error.

model validation standards. Thus, it is important to plan ahead and to consider every aspect of the model life cycle as part of the model development process.

VII. References

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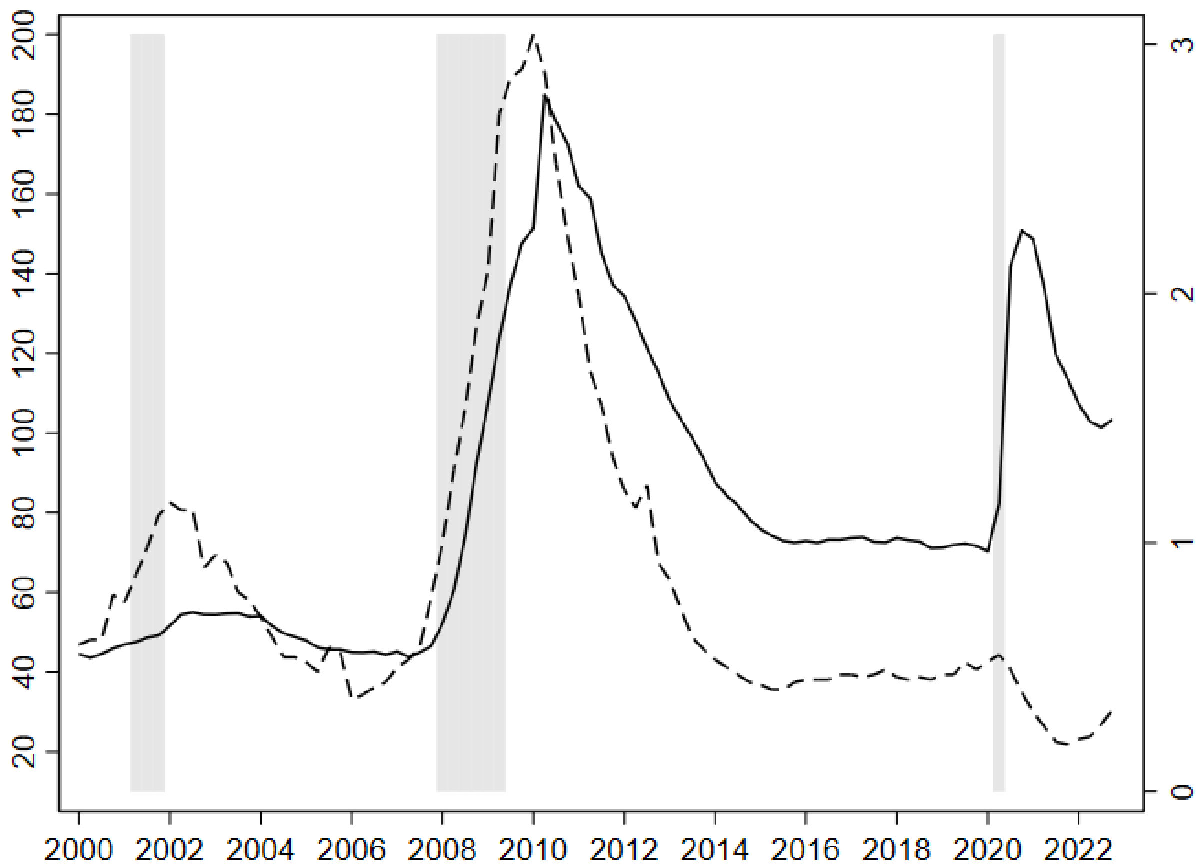
VIII. TABLES AND FIGURES

Figure 1: Historical Allowances and Charge-Off Rates

The figure depicts the aggregated charge-off rate on all loans at all commercial banks (dashed line, right axis) and allowances for loan and lease losses, large domestically chartered commercial banks (solid line, left axis).[41]

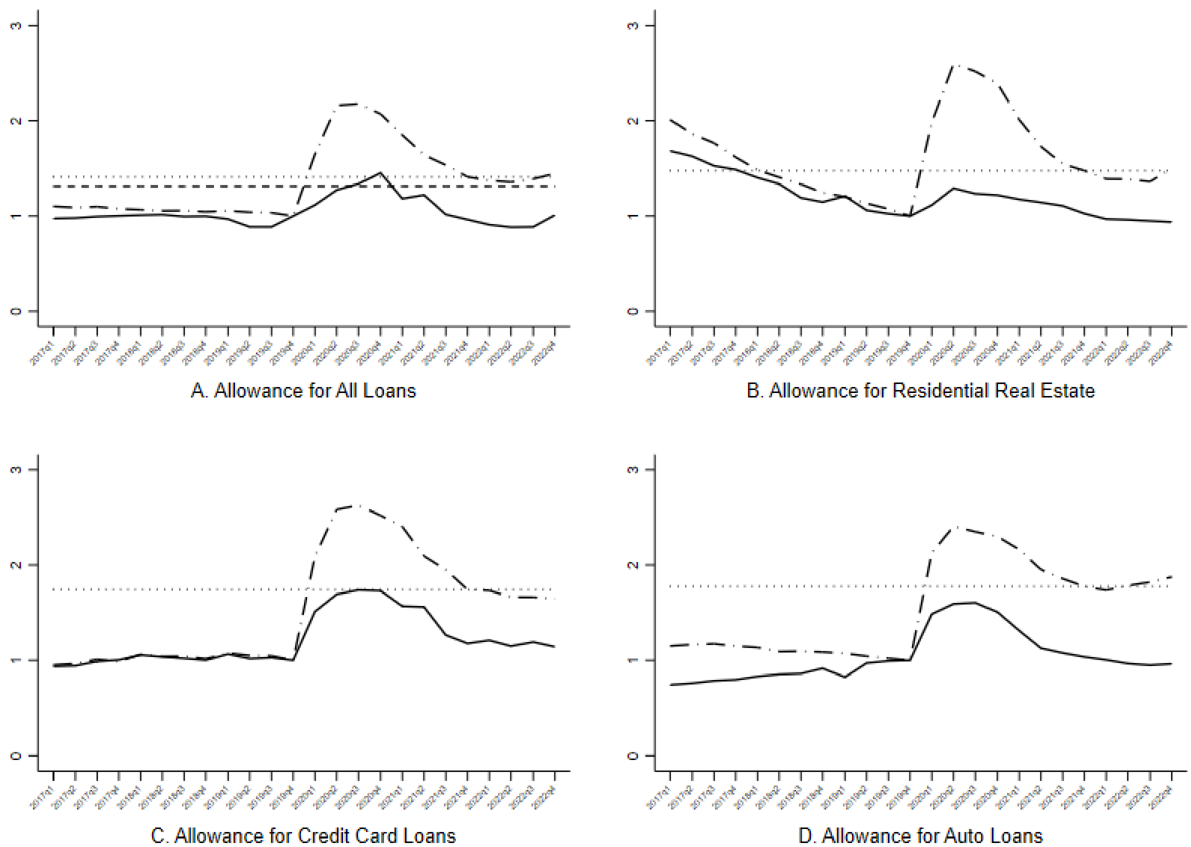


Data source: Charge-Off Rate on All Loans, All Commercial Banks (CORALACBN), FRED St. Louis Fed (stlouisfed.org).
Allowance for Loan and Lease Losses, Large Domestically Chartered Commercial Banks (ALLLCBW027SBOG), FRED St. Louis Fed (stlouisfed.org).

[41] The allowance for all commercial banks follows a similar pattern to the allowance for large commercial banks. We report the allowance for large commercial banks here because of the availability of historical data in FRED before the Great Recession.

Figure 2: ALLL During the Pandemic, CECL Adopters and Nonadopters

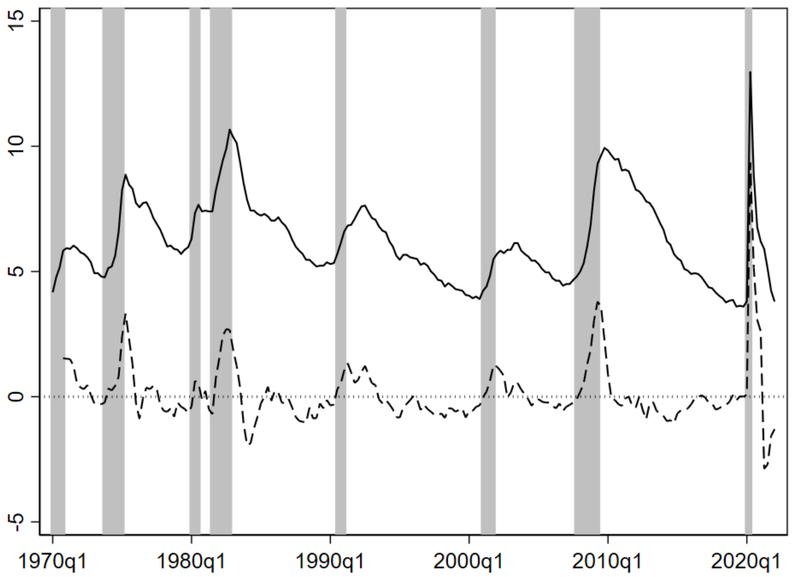
Allowances reported as a percentage of the allowances in the fourth quarter of 2019 for CECL adopters (dash/dot-dash line) and CECL nonadopters (solid line). We include the day one impact in graph A (dash horizontal line). Also, as an additional reference, we include the CECL allowances in the fourth quarter of 2021 (dotted horizontal line), a quarter of mild economic conditions.



Data source: Y9C public submissions.

Figure 3: Professional Forecasters' Error

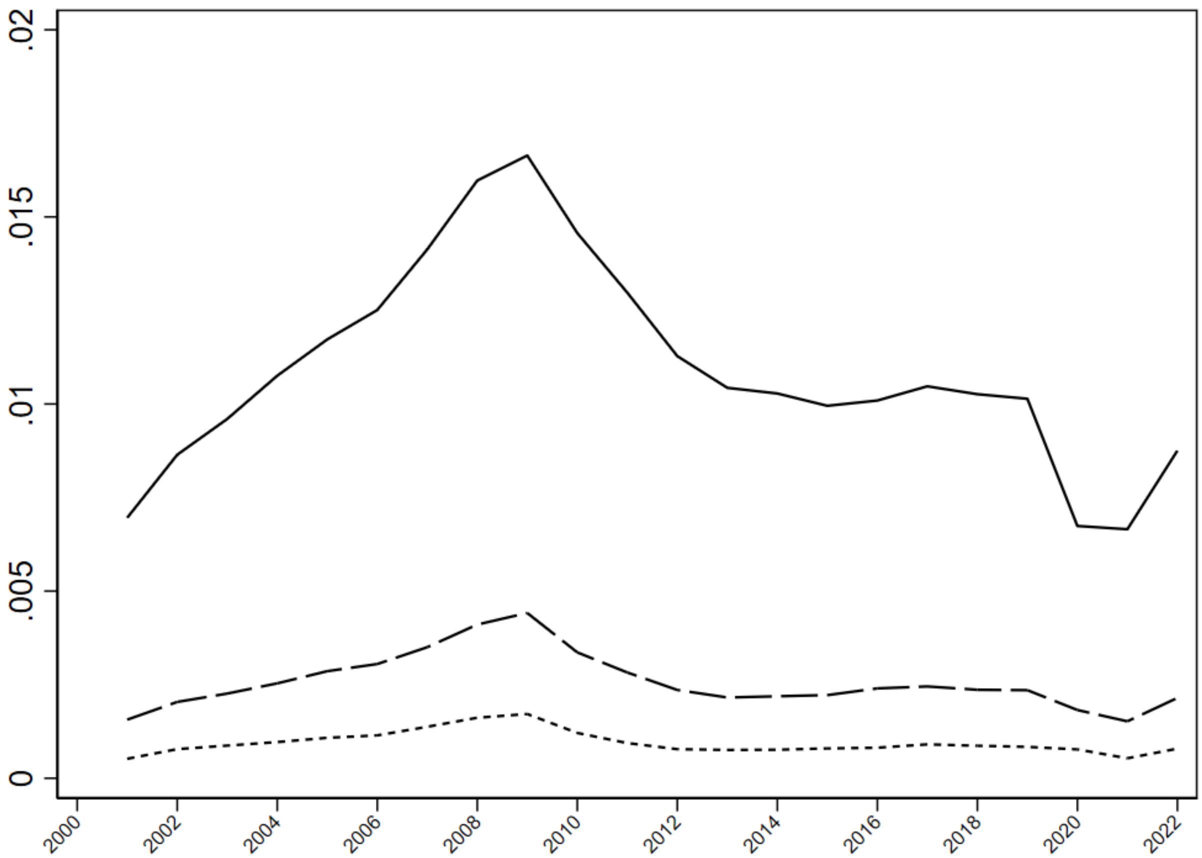
The figure depicts the realized unemployment rate, the four-quarter ahead unemployment rate forecast, and the forecast error. Forecasts are from the Philadelphia Fed's *Survey of Professional Forecasters*.[42] The solid line represents the unemployment rate; the dashed line represents the one-year-ahead unemployment forecast error. The forecast error was 4 percent during the Great Recession and up to 9 percent during the COVID-19 lockdown.



[42] Figure from "From Incurred Loss to Current Expected Credit Loss (CECL): A Forensic Analysis of the Allowance for Loan Losses for Credit Cards Portfolios," *Journal of Credit Risk* 16:4, December 2020.

Figure 4: 30+, 60+ and 90+ delinquency rates.

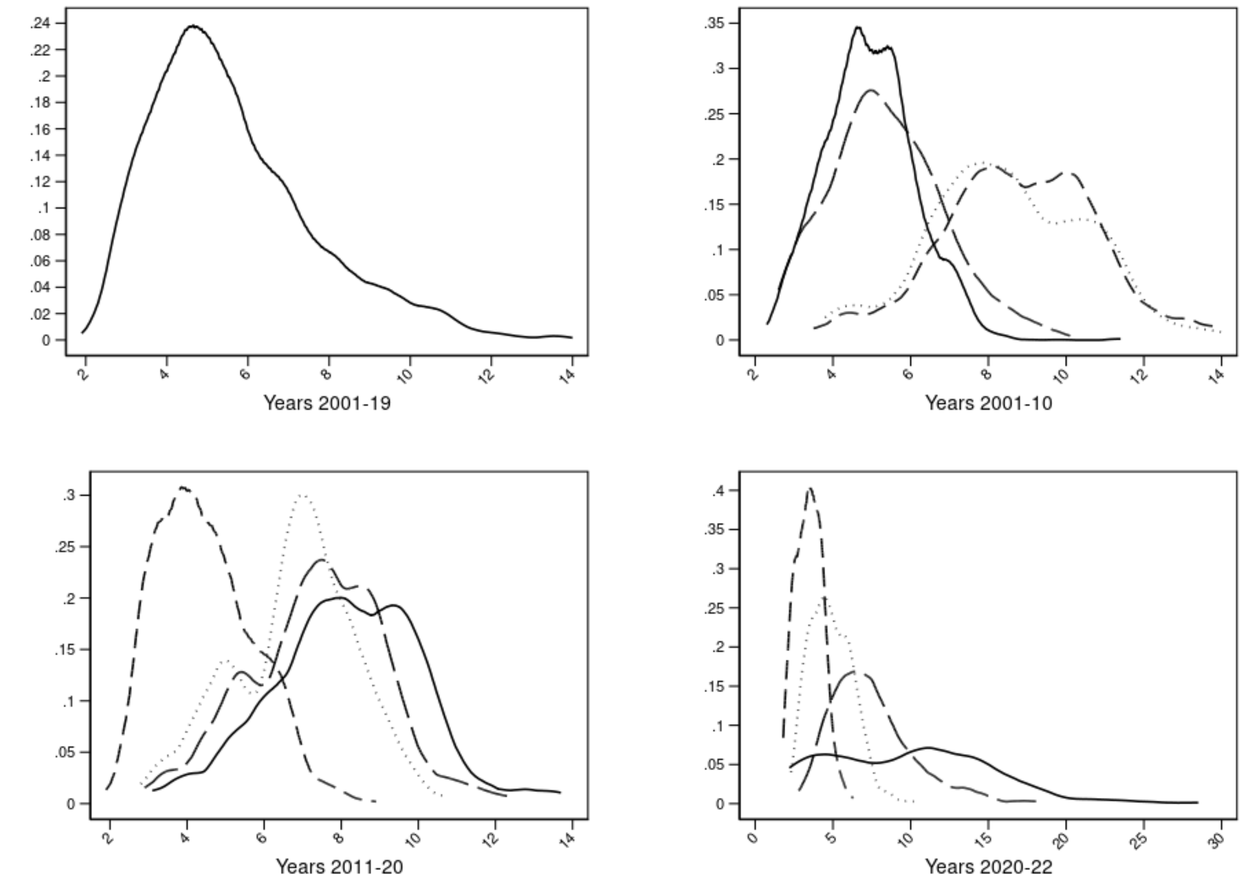
The figure depicts changes over time in 30+, 60+ and 90+ delinquencies in auto loans, represented by dots, dashes and a solid line respectively.



Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 5: State Unemployment Rate Over Time

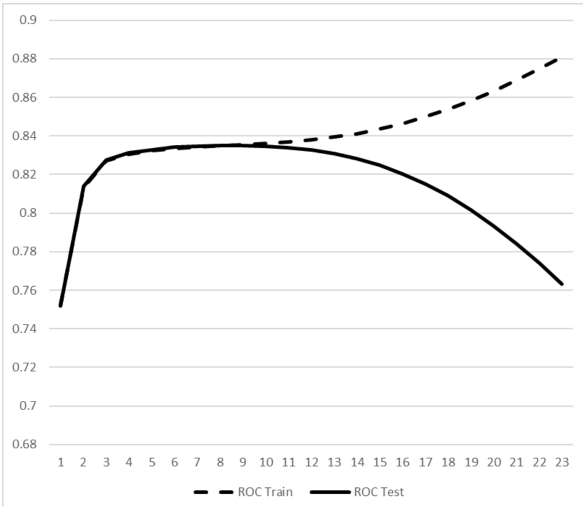
The charts depict kernel density functions that illustrate the variation in the unemployment rate over time and across states for different time periods. The top figures depict the distribution of state unemployment rate over the periods 2001–19 and 2001–10, respectively. The top-right figure depicts the distribution of state unemployment for the periods 2001–07 (solid line), 2008 (long dashed line), 2009 (dotted line) and 2010 (dashed line). The bottom-left figure depicts 2011 (solid line), 2012 (long dashed line), 2014 (dotted line) and 2014 to the first two months of 2020 (dashed line). Finally, the bottom-right figure depicts March 2020 to May 2020 (solid line), June 2020 to December 2020 (long dashed line), full-year 2021 (dotted line), and full-year 2022 (dashed line).



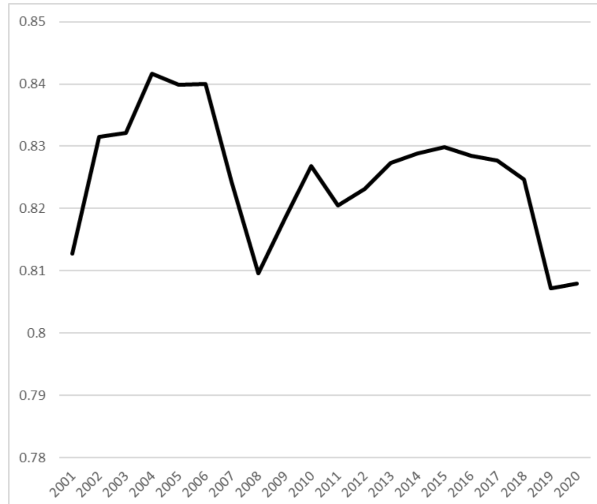
Data source: Bureau of Labor Statistics.

Figure 6: ROC Performance Across Models and Over Time

The figure on the left depicts receiver operating characteristic (ROC) metrics for a decision tree classifier of the two-year forward-looking default, as the maximum depth of the tree increases from one to 23, for test (solid line) and training (dotted line) data sets from the overall population of auto loan originations in the credit bureau from 2001 to 2020. The figure on the right depicts the ROC of the selected classification tree across cohorts.



a.- ROC performance across models.

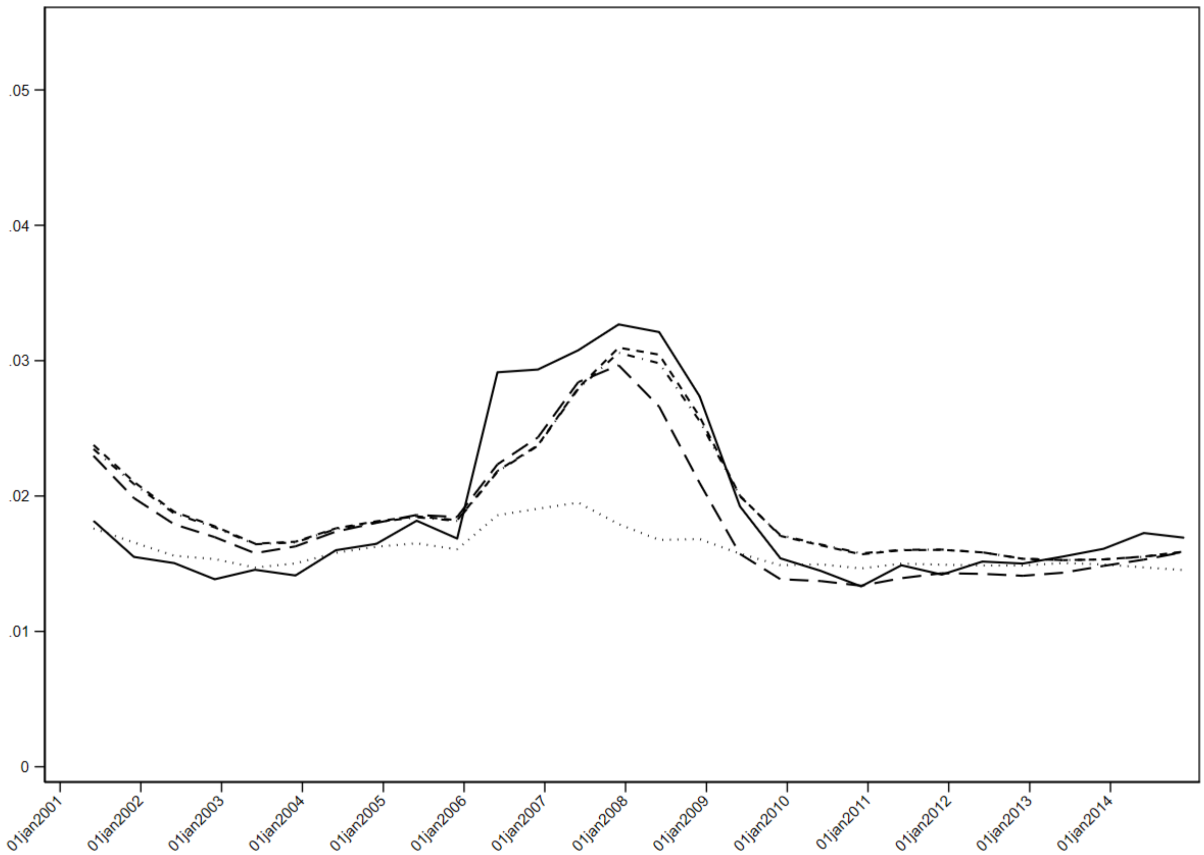


b.- Two-year ROC performance over time.

Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 7 Cumulative Default Rates Across Cohorts

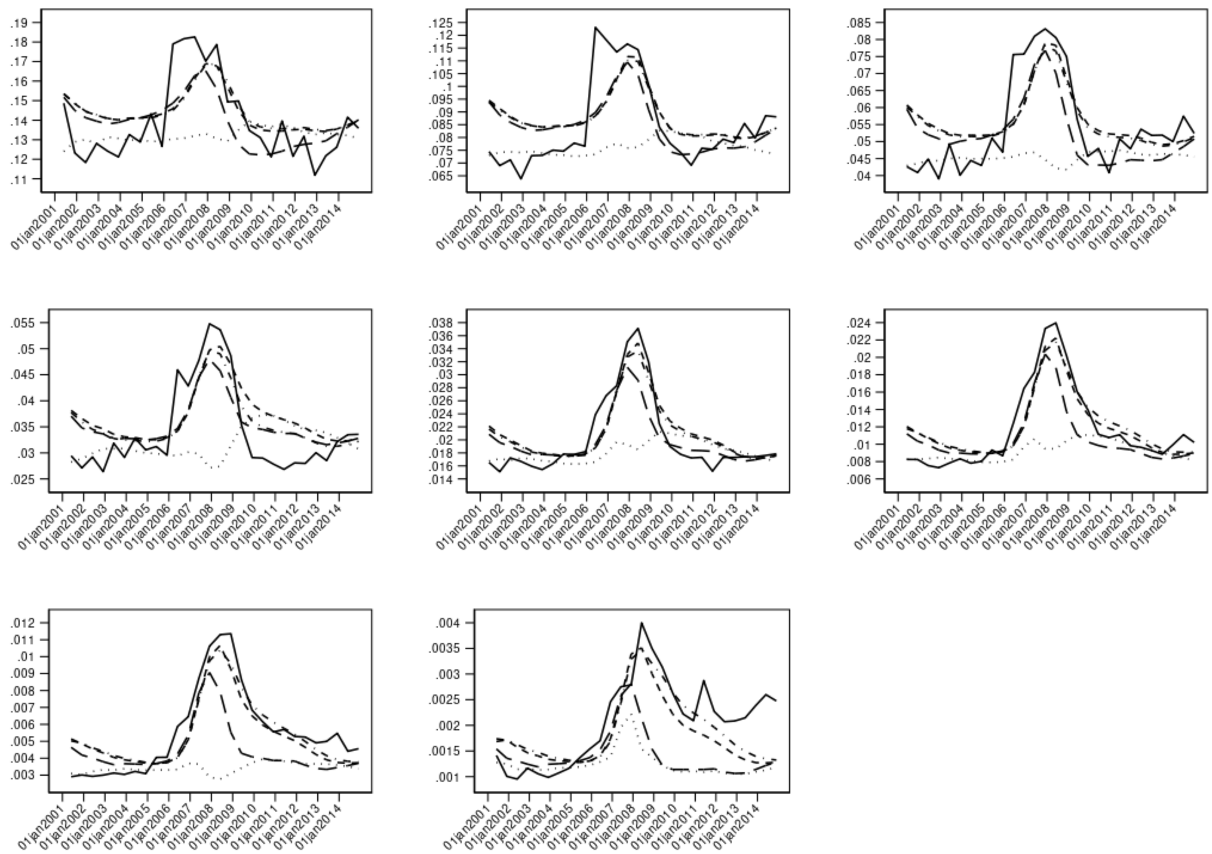
The figure depicts realized nine quarters cumulative default rates across cohorts (solid line), as well as forecasted values for models estimated with data including nine quarters of performance from the 2001-05 cohorts (dotted line), 2001-07 cohorts (long dash line), 2001-08 cohorts (dash line) and 2001-09 cohorts (dot-dash line).



Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 8 Cumulative Default Rates Across Cohorts and Risk Segments

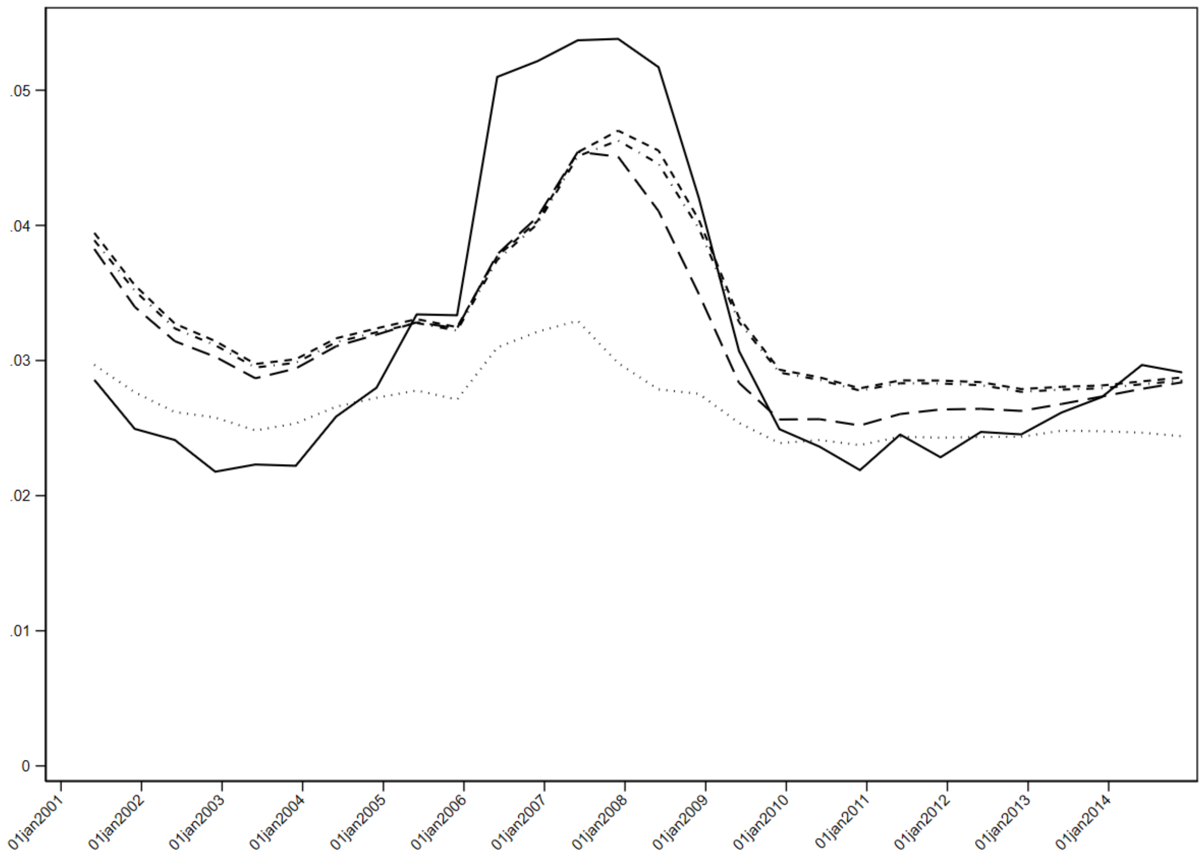
This figure expands on figure 7 by depicting cumulative default rates across risk segments, for segments with decreasing risk from left to right and from top to bottom. Each individual chart depicts the realized nine-quarter cumulative default rates across cohorts (solid line), as well as forecast values for models estimated with data including nine quarters of performance from the 2001–05 cohorts (dotted line), 2001–07 cohorts (long dashed line), 2001–08 cohorts (dashed line), and 2001–09 cohorts (dot-dash line).



Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 9 Lifetime Default Rates Across Cohorts

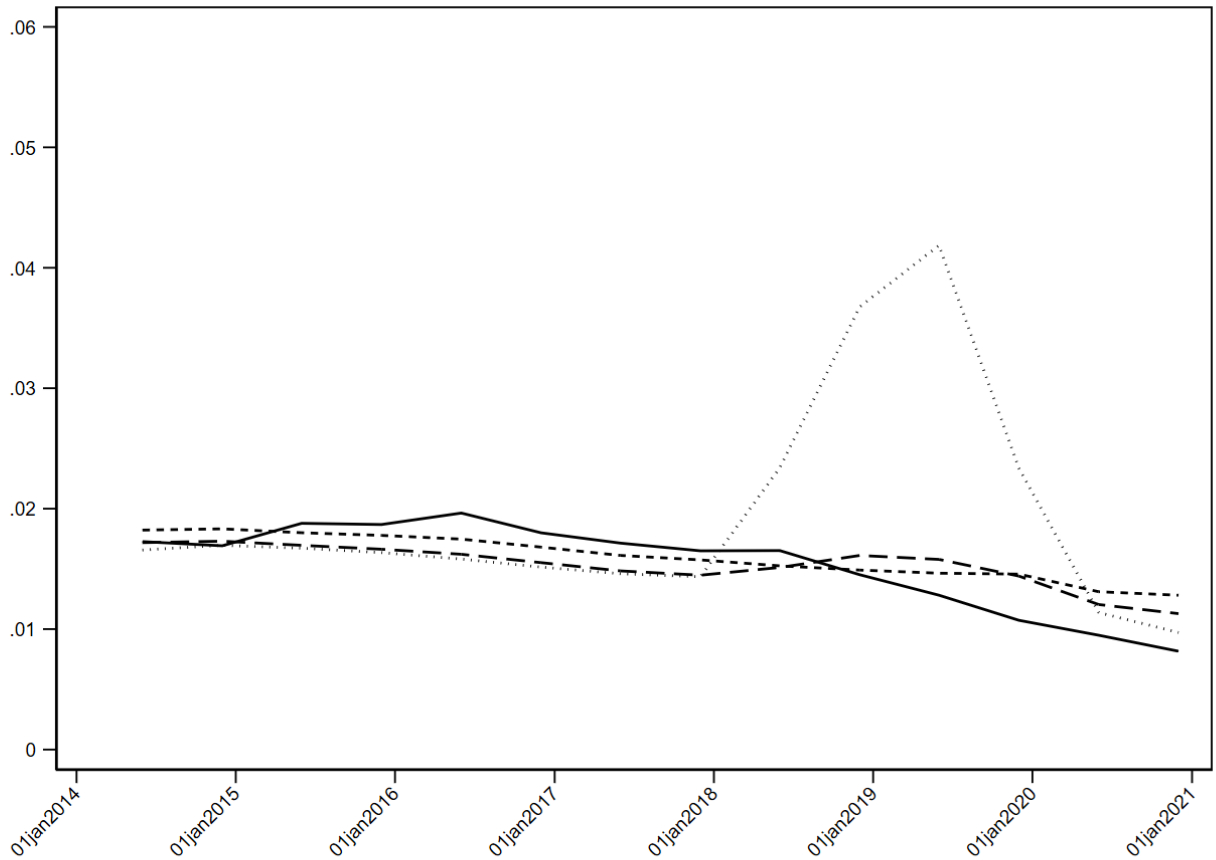
The figure depicts the realized lifetime cumulative default rates across cohorts (solid line), as well as forecast values for models estimated with data including nine quarters of performance from the 2001–05 cohorts (dotted line), 2001–07 cohorts (long dashed line), 2001–08 cohorts (dash line), and 2001–09 cohorts (dot-dash line). In the analysis, we define the life of the loan as the smaller of five years or time to payment.



Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 10 Cumulative Default Rates Across Cohorts Including the COVID-19 Period

The figure depicts the realized nine-quarter cumulative default rates across cohorts (solid line), as well as forecast values for models estimated with data including nine quarters of performance from the 2001–17 cohorts (dotted line), 2001–20 cohorts (long dashed line), and 2001–17 cohorts without macro variables (dashed line).

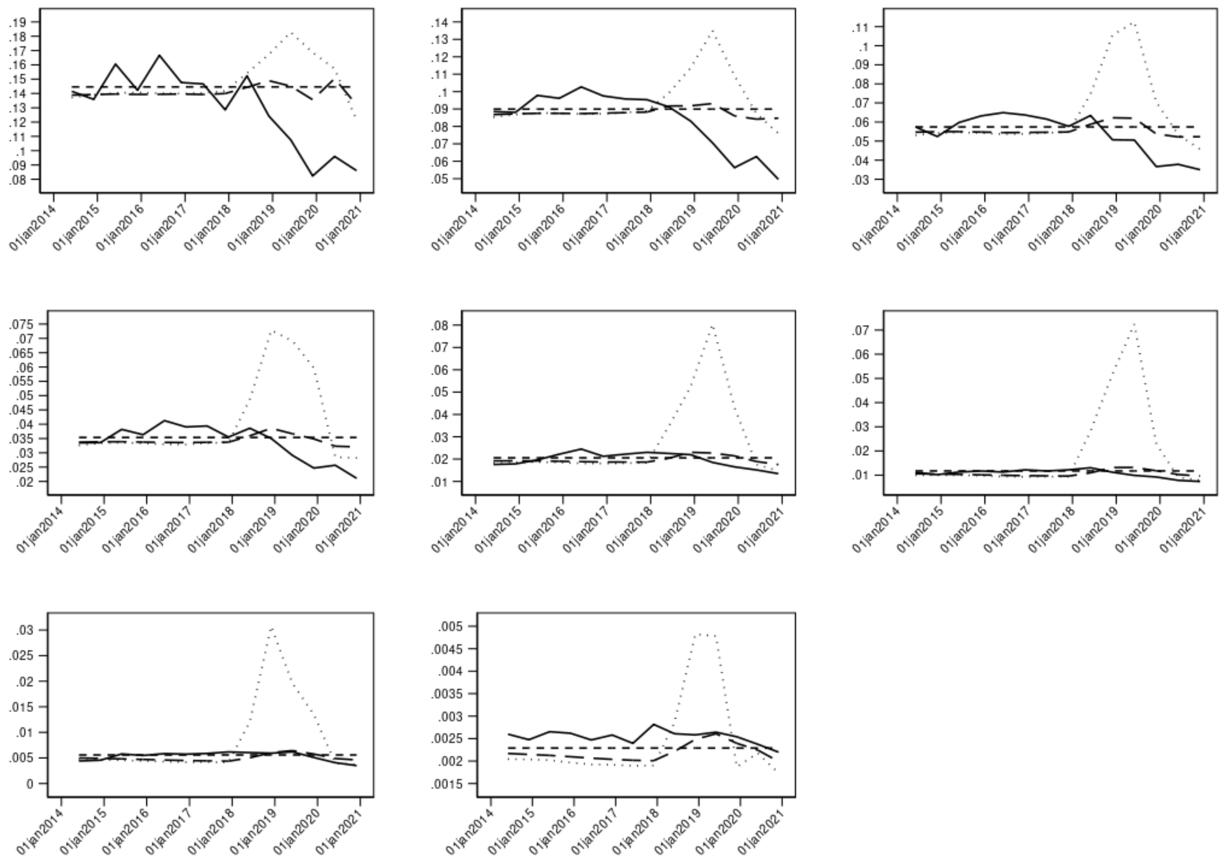


Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 11 Cumulative Default Rates Across Cohorts and Risk Segments,

Including the COVID-19 Period

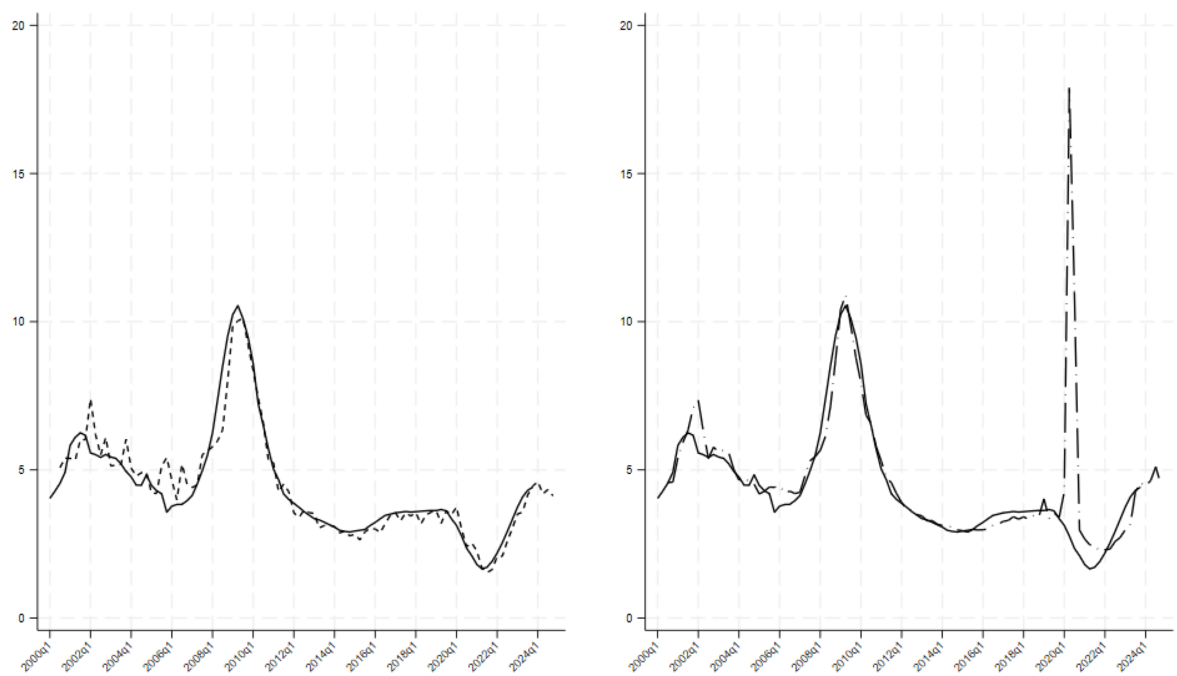
This figure expands on figure 10 by depicting cumulative default rates across risk segments, for segments with decreasing risk from left to right and from top to bottom. The figure depicts the realized nine-quarter cumulative default rates across cohorts (solid line), as well as forecast values for models estimated with data including nine quarters of performance from the 2001–17 cohorts (dotted line), 2001–20 cohorts (long dashed line), and 2001–10 cohorts without macro variables (dashed line).



Data source: Auto tradeline data from the FRBNY Consumer Credit Panel/Equifax.

Figure 12 Cumulative Default Rates Across Cohorts and Risk Segments, Including the COVID-19 Period

This figure expands on our work by analyzing the performance of credit cards portfolio leveraging a simple regression framework where one year forward cumulative charge-off rates are modeled as a function of lag risk drivers, including delinquency, charge-off, and macro variables (unemployment level and change). The figure depicts the realized four-quarters cumulative default rates across cohorts (solid line), as well as forecast values for models estimated with data including four quarters of performance from the period 2000–19 cohorts, projected to the 2001–24 period. The dash lines display projections from a model without macro drivers (short-dash) and a model with macro drivers (long-dash-dot).



Data source: https://www.federalreserve.gov/releases/chargeoff/

A. APPENDIX: Regulatory Guidance on CECL Implementation.

As FASB staff has indicated in multiple instances, the CECL standard allows for flexibility in determining the best approach for computing the allowance. CECL is by design nonprescriptive about the methodology that should be employed when computing the allowance, as well as the economic projections that should be considered when determining the reasonable and supportable forecast. This level of flexibility is intended to facilitate CECL implementation across financial institutions with different levels of complexity.

For the less sophisticated financial institutions, banking regulators have contributed examples of acceptable methodologies, like the snapshot/open pool approach, the vintage approach, and the remaining life/weighted average remaining maturity (WARM) approach.[43] The methods differ primarily on the way the lifetime historical charge-off rate is calculated. For example, the snapshot approach computes the lifetime historical charge-off rate as the ratio of total lifetime charge-offs associated with the snapshot loan portfolio to loan portfolio balance. Specific adjustments to current conditions, and reasonable and supportable forecasts should be considered when computing the CECL allowances using these simpler methods.[44] An FASB staff Q&A transcript clarifies that it is acceptable to adjust historical loss information for current and future forecast economic conditions through a qualitative approach properly documented.

The Federal Reserve has developed a simple Excel-based tool to assist smaller community banks with total assets of less than $1 billion in calculating their allowances under CECL. This method, known as SCALE (scaled CECL allowance for losses estimator), uses publicly available Call Report data to derive expected lifetime credit loss rates. The Federal Reserve has also developed an Excel-based expected loss estimator (ELE) tool for the WARM method, primarily intended for community financial institutions.[45] The method allows for the use of a financial institution's own loan data. WARM has been reviewed by FASB staff and deemed one of many methods that could be used to estimate allowances for less complex financial asset pools.

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[43] https://www.supervisionoutreach.org/cecl/methodologies-and-examples

[44] Additional details can be found in the following interagency slide presentation: www.supervisionoutreach.org/-/media/files/supervisionoutreach/cecl/22718-ask-the-regulator-presentation.pdf?sc_lang=en&hash=95EEAD092807060791975C482B16B553

[45] https://www.supervisionoutreach.org/cecl/ele

Complex financial institutions may consider more sophisticated model frameworks including discounted cash flow approaches, roll rate approaches, and methodologies that decompose losses in terms of the probability of default (PD), loss given default (LGD), and exposure at default (EAD). On the one hand, sophisticated modeling frameworks can better accommodate changes in portfolio characteristics and macroeconomic scenarios. On the other hand, they may be more sensitive to model and forecasting error that may be difficult to diagnose and troubleshoot, in part because of the intricacy of the modeling framework. Challenges to CECL models may be particularly severe in times of crisis.