CECL Implementation and Model Risk During the Pandemic

By José J. Canals-Cerdá[1]

Abstract

We discuss challenges faced by banks implementing the novel Current Expected Credit Loss (CECL) allowance methodology during the COVID-19 pandemic. Specifically, the focus is on the challenges of economic forecasting and model misspecification errors and its impacts on model risk and loss projection bias in crisis periods. Drawing from the advice of regulatory agencies and senior leaders, as well as basic econometrics principles, we highlight some lessons learned and areas of development. We advocate looking beyond statistical properties and emphasizing resiliency and adaptability of models, and model infrastructures, to new shocks and uncertain economic conditions.

[1] The views expressed here are solely of the author and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System.

The CECL Framework, a Brief Introduction

The Allowance for Loan and Lease Losses (ALLL) is an estimate of credit losses within a bank's portfolio of loans and leases used to reduce the book value of loans and leases to the amount that a bank expects to collect. Over the last 40 years, the standard approach employed for computing the ALLL under U.S. generally accepted accounting principles has been the incurred loss accounting methodology. Under this methodology, the allowance is a valuation reserve established and maintained to cover losses that are probable and estimable as of the reserve calculation date.[2] In the aftermath of the 2007–2009 Great Recession, the incurred loss methodology was criticized for its "failure to fully recognize existing credit losses earlier in the credit cycle."[3] Various stakeholders requested that accounting standard-setters work to enhance standards on loan loss provisioning to incorporate forward-looking information.[4] In June 2016, the Financial Accounting Standards Board (FASB) issued an accounting standard update (ASU 2016-13) — and a new ALLL methodology, the Current Expected Credit Loss Framework (CECL), was born.

CECL was adopted by some institutions by 2020, while others will be required to adopt it in 2023.[5] CECL represents a significant departure from the incurred loss standard that it replaces. It 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.[6] It also requires enhanced disclosures.[7] CECL is nonprescriptive about the models and

[2] See Statement of Financial Accounting Standards 114.

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

[4] Additional information can be found at https://www.federalreserve.gov/supervisionreg/topics/faq-new-accounting-standards-on-financial-instruments-credit-losses.htm.

[5] U.S. Securities and Exchange (SEC) filers, with the exception of smaller reporting companies, were required to adopt CECL on January 1, 2020, and other companies will be required to adopt CECL on January 1, 2023.

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

[7] 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.

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 and convergence to long-run economic conditions after that. At a very high level, CECL considers the analysis of lifetime losses on a static portfolio at a specific time.[8]

Intuitively, both the incurred loss approach and the CECL framework impose specific restrictions on the ALLL. Specifically, the incurred loss framework bars the recognition of losses beyond incurred losses, while the CECL framework requires the recognition of expected future lifetime losses under some additional assumptions. Methodological or regulatory constraints on the ALLL do not directly impact the amount or timing of losses.[9]

Projections of CECL Impact Prior to Implementation

By delaying the recognition of loan losses during the Great Recession, the incurred loss framework contributed to the buildup of allowances in the middle of the stress period. This way, it could have contributed to a decrease in bank lending and to the overall procyclicality of the financial system. These concerns were identified by the Financial Stability Forum (FSF) in its 2009 report on procyclicality in the financial system.[10] The FSF indicated that earlier recognition of loan losses could help lessen procyclicality while enhancing the consistency of information provided to investors.

A recent Bank of International Settlements (BIS) working paper (WP-39) conducted a review of the literature on CECL and the International Financial Reporting Standard 9 (IFRS 9). It reviewed 37 papers with a special focus on the topic of the procyclicality of loss provision. It differentiated between two main forms of procyclicality. First, the concept of procyclicality of more pressing interest to policymakers considers a causal feedback loop between the allowance framework and the economic cycle. In general, it is very difficult to ascertain causality because of complex interactions among banking regulations, economic policy, and economic activity, as well as data limitations. Second, research studies most often analyze the statistical comovement

[8] See https://www.federalreserve.gov/supervisionreg/topics/faq-new-accounting-standards-on-financial-instruments-credit-losses.htm.

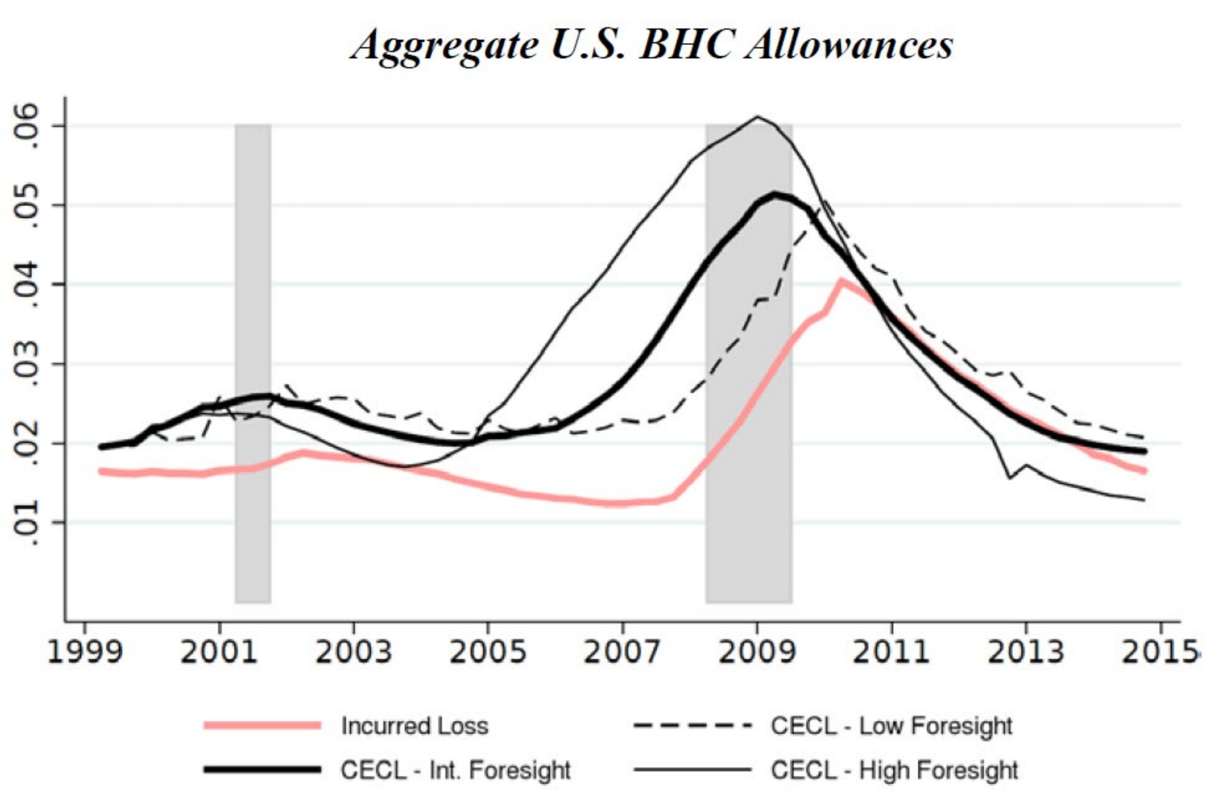
[9] See Question 3 in https://www.federalreserve.gov/supervisionreg/topics/faq-new-accounting-standards-on-financial-instruments-credit-losses.htm.

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

between allowances and the business cycle; BIS WP-39 refers to this as cyclicality to differentiate it from the causal interpretation.

It seems clear that CECL is subject to cyclical behavior quasi-by-design, as expectations about the severity of credit loss are likely to move in tandem with a deterioration of economic conditions. However, the degree of cyclicality will be conditional on the level of forecasting accuracy in anticipation of a downturn as Loudis and Ranish (2019) show (**Figure 1**). They consider three different foresight scenarios that attempt to represent different levels of foresight that banks estimates may reflect (Loudis and Ranish, 2019). Under perfect forecast of economic conditions, financial institutions will be able to adjust their allowances in anticipation of a downturn, while a myopic forecast will necessitate a significant increase in allowances over the unanticipated downturn. This level of flexibility in the CECL framework was not present in the incurred loss framework, which didn't allow for the recognition of expected future losses beyond incurred losses.

Figure 1: CECL Projections During the Great Recession



Note: This figure is from Loudis and Ranish (2019).

There was broad agreement among studies on the assertion that if CECL had been adopted prior to 2007, the banking industry would have accumulated higher reserves in the early days of the Great Recession. There was also broad agreement that peak levels of allowances during downturns would have been higher under CECL, as the allowance in that case is defined over the life of the loan. These views are also broadly consistent with the experience of CECL adopters in the U.S. during the recent COVID-19-induced economic downturn, as we discuss in the next section. There seems to be also agreement that CECL adds flexibility to the ALLL when compared with the incurred loss framework and that it may add transparency to financial statements through enhanced disclosures. Studies prior to the CECL implementation generally also agreed on a relatively modest average "day one" impact of CECL, unless the economy was in the early stages of a recession.[11]

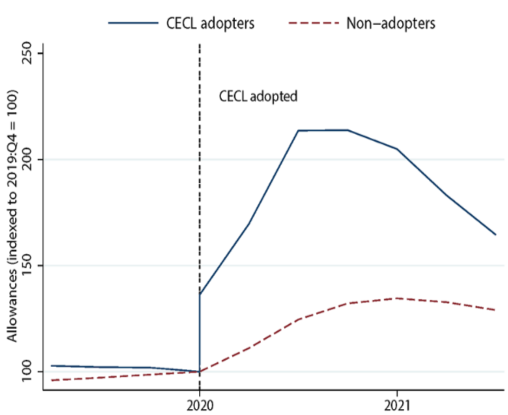
There was no broad agreement on the impact of CECL adoption on lending. Some authors argued that lending would be impacted if financial institutions are required to significantly increase their allowances during downturns (Covas and Nelson, 2018). While others argued that with enough hindsight, the added flexibility of CECL would allow lenders to build additional allowances prior to the downturn, or early in the downturn, and this could limit the impact on lending (DeRitis and Zandi, 2018). Figure 1 highlights the difficulties in reaching a firm conclusion about this topic. The buildup of allowances prior to a crisis will be conditional on the level of economic foresight about the likelihood and severity of a downturn. High foresight leads to early buildup of allowances in anticipation of a downturn, while low foresight leads to the buildup occurring during the downturn. While CECL may be subject to cyclicality, it is harder to ascertain its level of procyclicality, taking into account that expectations about future losses have a direct impact on lending decisions regardless of the allowance methodology. Loudis and Ranish (2021) find no significant evidence of a direct impact of CECL on lending during the COVID-19 crisis, although this particular downturn was unusual by its level of government support to consumers and businesses and because banking regulations were temporarily adjusted to accommodate concerns about CECL implementation (Wall, 2020).

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

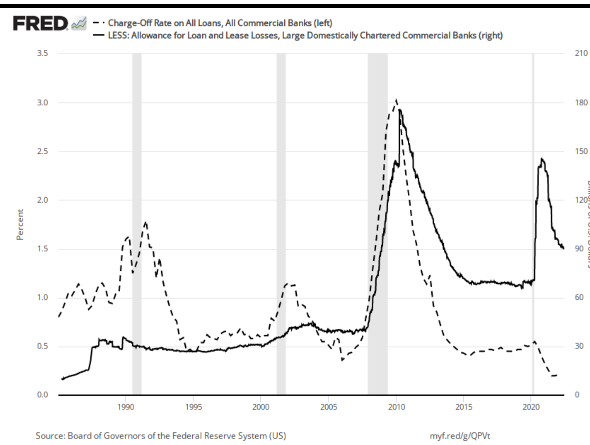
CECL in the Times of COVID-19

The COVID-19 pandemic and its impact on the economy and credit markets created significant challenges for CECL in the U.S. and IFRS 9 in other jurisdictions. The impact of COVID-19 on the economy in the early days of the pandemic was significant as a direct result of the pandemic in addition to policy responses in the form of lockdowns and monetary and fiscal policy.[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 an average rate of about 1 percent monthly, reaching a rate below 4 percent by the end of 2021. Other macroeconomic indicators were also significantly impacted. During this time, economic and financial forecasts deteriorated significantly.

Figure 2: The ALLL During the Pandemic



a. Adopters vs nonadopters (Figure 3 from Loudis, Pechenik, Ranish, Vojtech and Xu, 2021).



b. ALLL vs. Charge offs. Data source https://fred.stlouisfed.org/.

Figure 2.a depicts the behavior of allowances for CECL 2020 adopters and nonadopters during the early days of the pandemic.[13] As Loudis, Pechenik, Ranish, Vojtech, and Xu (2021) indicate: "The adoption of CECL resulted in an immediate 37 percent increase in adopters' allowances on January 1, 2020. As the pandemic stressed the economy, CECL adopters rapidly increased loss provisions. Not counting the adoption impact, allowances increased by 76 percent

[12] Pinello and Puschaver (2020) provide a financial account of the challenges faced by CECL adopters in the first quarter of 2020. Wall (2020) provides additional information about regulatory efforts to minimize the impact of CECL in the early days of the pandemic.
[13] Original graph in Figure 3 is from Loudis, Pechenik, Ranish, Vojtech, and Xu (2021).

in the first half of 2020 relative to 2019:Q4 levels. In comparison, non-adopters' allowances increased by only 32 percent over the same period. After peaking in 2020:Q2, CECL adopters' allowances started to decline with improvements in the economic outlook. Nonadopters' allowances peaked in 2020:Q4, and have only declined slightly since then. As of 2021:Q2, the difference in allowances between CECL adopters and non-adopters is back to where it was immediately after CECL adoption." Thus, CECL allowances increase significantly early in the pandemic, perhaps as a combination of added flexibility of the CECL framework and more extensive provisioning requirements, and then also decrease significantly in the following quarters.[14] 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 procyclicality. However, the COVID-19 pandemic represented a unique economic shock that was difficult to forecast, and this contributed to an increase in allowances that was consistent with the myopic case in Figure 1.

Figure 2.b depicts changes in the ALLL for all commercial banks over the period 1985–2022 at the aggregate level. The figure also illustrates the relationship between allowances and charge-offs over the same period. 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 that did not peak until early 2010. In contrast, charge-off rates during the period of the COVID-19 pandemic decreased with respect to the already record-low levels of recent years. This difference in charge off performance across two different episodes of stress is difficult to reconcile without considering the unprecedented fiscal and monetary policy responses experienced during the pandemic.

A recent BIS newsletter offers a window into the strategies leveraged by financial institutions to mitigate model risk and adapt their credit risk modelling policies and practices.[15] Consistent with our analysis, the newsletter reports that credit performance during the pandemic period deviated considerably from historical patterns and trends. In response, banks applied sizeable judgment-based adjustments (overlays and overrides) to both their Basel Internal

[14] Beck and Beck (2022) report the same performance of provisions across CECL adopters and nonadopters and suggest that this represent preliminary evidence that ASU 2016-13 has achieved its objective of making allowances more sensitives to changing economic conditions.

[15] See the newsletter on COVID-19-related credit risk issues (bis.org).

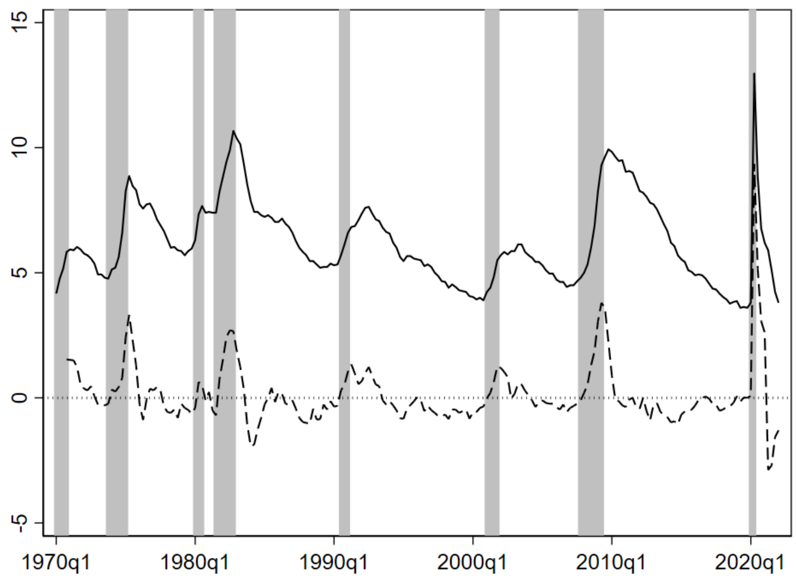
Ratings Based approach to capital requirements and provisioning models. It also highlights that controls and governance around model adjustments could be improved. Supervisors observe three main challenges in relation to banks' provisioning models: first, challenges around controls regarding model risk management and data; second, challenges capturing economic uncertainty; and third, challenges identifying credit deterioration in vulnerable sectors and borrowers. Observed adopted approaches to model development included: (1) exclusion of COVID-19-related data, primarily because of 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 vs defaults); (3) enhanced infrastructure and data feeds to ensure the relevant data are fully understood and properly integrated into analysis of decision-making systems. Looking at the future, the newsletter underscores that both supervisors and banks are grappling with how to incorporate and reflect data over the COVID-19 period in credit risk models going forward.

CECL Sensitivity to Economic Forecasting Error

CECL allowances represent forward-looking estimates of credit losses, with reasonable and supportable forecasts playing an important role in its calculation. Thus, it should be no surprise that the impact of economic forecasting error could have been substantial during the COVID-19 pandemic.[16] In this section, 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 variable across many portfolios. **Figure 3** displays historical realized unemployment rate for the period 1970–2022; the figure also displays the level of the one-year-ahead average forecasting error from the *SPF*. Prior to the COVID-19 pandemic, the largest one-year-ahead forecasting error was 4 percent 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.

[16] 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.

Figure 3: Professional Forecasters Error



Note: The figure depicts realized unemployment rate, four-quarter ahead unemployment rate forecast and the forecasting error. Forecasts are from the Philadelphia Fed's *Survey of Professional Forecasters*.[17] 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.

The impact of economic forecasting errors on allowances are unlikely to be homogeneous. They will vary across portfolios and within risk segments of a portfolio and may also vary as a function of model specific assumptions. The disconnect between allowances and charge-offs in Figure 2.b affects both the CECL and incurred loss frameworks, but as the Figure 2.a shows, the effect is particularly pronounced for CECL adopters. Model accuracy is desirable in principle, and one cannot always expect model projections to be conservatively inaccurate. In addition, model accuracy impacts a second objective of CECL, which is balance sheet transparency.[18] Thus, based on the experience from the two most recent crisis episodes, we can expect economic forecast uncertainty to increase significantly during crisis episodes and CECL projections to be significantly impacted.

[17] 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.*

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

CECL Sensitivity to Model Error

While model underperformance during periods of stress may be unavoidable, it is important to understand the roots of the problem and to better prepare for future crises. A better understanding of the sources of model bias can help address model shortcomings with the aid of adjustments and overlays, and it can also contribute to a better design of models and model infrastructures that are resilient to shocks. One reason for the presence of bias in CECL projections already discussed is the problem of significant error in reasonable and supportable forecasts during periods of economic stress. Another reason less often discussed and potentially more detrimental is the problem of model misspecification error. A model represents an approximation to a certain data-generating process. As a result, virtually all models are misspecified at some level with the rare exception of models deployed in highly controlled environments.[19]

Typical sources of model misspecification are functional form misspecification and omitted variables. One could argue that the problem of omitted variables was particularly important during the pandemic. Specifically, models trained with historical data over the period of the Great Recession were unequipped to forecast the economic impact of a pandemic as well as the effects of fiscal and monetary policy actions. Thus, it is perhaps not surprising to observe a disconnect between allowances and charge-offs in the early months of the pandemic, as depicted in Figure 2.a.[20] The intensity of the shock contributed to the severity of economic outcomes, while significant government support contributed to lessen the severe of economic outcomes, which was also commensurate with the intensity of the shock.[21]

The problem of model misspecification is well understood in econometrics. Model misspecification error can lead to biased projections, even in the case of accurate economic forecasts. As a rule of thumb, model bias increases with the severity of misspecification. Thus, it

[19] Model misspecification and forecasting error are not the only sources of variation in CECL projections, see, for example, Breeden (2018) or Canals-Cerdá (2020).

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

[21] 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). Results in Degryse and Huylebroek (2022) are consistent with a positive impact of government fiscal policy on banks' credit risk and profitability.

is not surprising that the significant government interventions unaccounted for in models lead to significant bias in model projections. Econometric theory also suggests that model factors that have the largest correlations with relevant unaccounted factors will be more impacted by misspecification bias.

Mitigating the Impact of Forecasting and Model Error

Underperformance of CECL models may arise not only as a result of measurement error in macroeconomic forecasts but as a result of a more fundamental problem of model misspecification error. In these cases, it may be necessary, or required, to modify and adapt models to the novel environment. The specific models to be considered in periods of stress can be guided by data analysis, by expert judgment and by insights from econometric theory.[22]

How can we mitigate CECL sensitivity to model and forecasting error? A recent speech from Governor Christopher J. Waller offers some lessons.[23] The speech stresses three main recommendations for forecasters that also broadly apply to CECL projections. First, "forecasters need to approach this work with humility"; second, "past behavior is not always a good predictor of future behavior"; and third, "Economic forecasting is a pretty hopeless endeavor. So why do we do it? Because of how much is riding on the outcome."

Waller's speech also offers advice for tackling challenges beyond forecasting error that often appear during periods of economic stress arising from unprecedented circumstances. His first piece of advice is: "[W]hen the shock is unique, adapt fast." This requires careful analysis of the novel shocks and modifying and adapting models to the novel environment. His second piece of advice relates to the significant or even immense uncertainty that accompanies a unique novel shock, like the shock triggered by a pandemic. Specifically, Waller points out that "novel shocks can produce financial stress in unexpected areas." This was certainly the case during the Great Recession with the propagation of a real estate shock to other areas of the financial landscape.

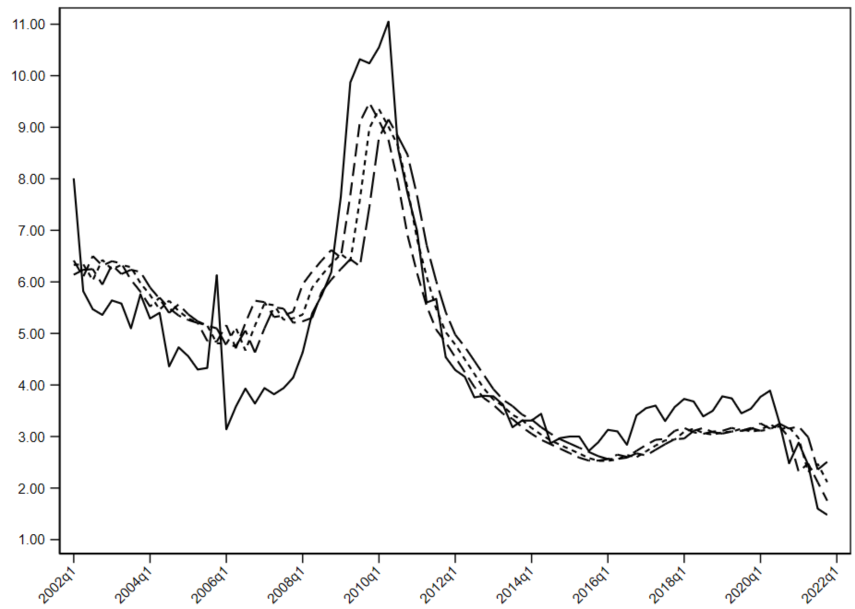
[22] Model misspecification during crisis is only one possible source of forecasting bias. For example, measurement error in input variables broadly defined could be considered as another candidate for further analysis.

[23] Governor Christopher J. Waller (2021). "A Hopeless and Imperative Endeavor: Lessons from the Pandemic for Economic Forecasters." Speech at the Forecasters Club of New York, December 17.

This was also the case during the pandemic with the impacts on the supply chain that have continued for several years and its effects on financial conditions, inflation in particular.

Economists have also warned against over-reliance on a single model. Specifically, Larry Summers said, "policymakers in economics who go wrong the most are the ones who are most confident of a single model."[24] In fact, generally, while models conditional on macroeconomic factors performed poorly, not all relationships "broke down" during COVID-19.

Figure 4: Credit Card Charge-off Rate Fitted to Delinquency Rate Lags



Note: Here are realized charge-off rate (solid line) and fitted charge-off rate (dotted-lines). In sample 2002–2019, out of sample 2020–2022. Models estimated with 2, 3, and 4 quarters delinquency rate lags. Source: https://fred.stlouisfed.org/.

For illustrative purposes, **Figure 4** depicts the relationship between realized credit card charge-offs and projections from models fitted to delinquency rate lags using publicly available data. We observe that models of credit card charge-off fitted to one to four quarter lags performed reasonably well during the period 2020–2022. These types of simple models can act as benchmarks or early warning models to primary models, can offer guidance when overrides

[24] See https://www.youtube.com/watch?v=t4v-L8WiFf0. Larry Summers, November 12, 2021, Bloomberg News. Larry Summers was talking about inflation, not about CECL.

or overlays are applied to primary models, or can serve as a platform to open a dialogue with senior managers, auditors, or regulators.

While we argue in favor of a flexible model infrastructure, we should acknowledge the challenges of this strategy, especially for heavily regulated financial institutions. A recent report (McKinsey & Company, 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. Furthermore, the inventory of models at financial institutions continues to grow at a rate of about 25 percent over the last three years. Undoubtedly, validation resources get strained during periods of crisis. The report also points to the importance of automation of model-risk-management workflows, as well as managing validation frequency.

Final Thoughts

The pandemic presented novel challenges to the recently implemented CECL framework, which relied heavily on the tools of credit risk modeling and economic forecasting. It also presented unforeseen challenges to credit risk models more generally, as highlighted in a recent BIS newsletter (2022). This points to a tension in periods of significant economic uncertainty between the risk management principle of conservativism and the CECL aspirational principle of balance sheet transparency.

We can build on the lessons learned during the pandemic and the Great Recession to improve the design of credit risk models and model infrastructures. Models are likely to underperform again in a future crisis because they are imperfect representations, or abstractions, of observed processes. In the case of the recent crisis, unprecedented lockdown policies and fiscal and monetary policy undoubtedly played a role in the credit risk performance of loan portfolios and the underperformance of models.

As indicated in a recent speech by Waller, "[W]hen the shock is unique, adapt fast." Model specifications more robust to crises may not necessarily be selected on the basis of statistical performance alone. Parsimonious and interpretable models may be more easily troubleshooted, and nimble model infrastructures may prove more useful in periods of crisis, which may require models to be recalibrated and perhaps also respecified. Novel data may be brought in to improve model performance, to mitigate sources of model bias, or to offer support to other types of model adjustments.

Some economists have also cautioned about overreliance on the predictions of a single model. Different model specifications may capture distinct aspects of an observed phenomena; some models may be more robust to shocks, while others may be more accurate when properly specified. Some alternative models may serve as a benchmark or challenger to primary models, or even offer a simple sanity check when current experience deviates significantly from past experience.

It is important to look beyond the statistical framework and to account for the resiliency and adaptability of models to new shocks and uncertain financial conditions. This has led to a new appreciation for the virtues of simple models. They can facilitate better understanding of the impact of "shocks" or "black swans," can be more easily troubleshooted, and can offer guidance when considering judgmental adjustments, overrides, or overlays to an existing modeling framework or when building more complex models.

Rather than disregarding data generated during periods of crisis because it does not conform to the status quo, or because the crisis is unlikely to present itself again in the same form, we should treasure it and use it to better understand the challenges that a crisis can present to the robustness of our models and model infrastructures, as well as to preemptively develop a playbook on how to better respond to the unavoidable crisis episodes that the future will present.

References

Bank of International Settlements (2021). “The Procyclicality of Loan Loss Provisions: A Literature Review,” Bank of International Settlements Working Paper 39.

Bank of International Settlements (2022). “Newsletter on COVID-19 Related Credit Risk issues,” https://www.bis.org/publ/bcbs_nl26.htm.

Beck, A. K., and P. J. Beck (2022). “Effects of ASU 2016-13 and COVID-19 on Banks' Loan Loss Allowances.” *Advances in Accounting* 56, 100581.

Breeden, J. (2018). “CECL Procyclicality: It Depends on the Model.” Prescient Models LLC, www.prescientmodels.com/articles/CECL-Procyclicality.pdf.

Chae, Sarah, R. Sarama, C. Vojtech, and J. Wang (2018). “The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves.” Finance and Economics Discussion Series Working Paper 020, https://www.federalreserve.gov/econres/feds/files/2018020pap.pdf.

Canals-Cerdá, J. (2020). “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.

Chen, J., Y. Dou, S. G. Ryan, and Y. Zou (2022). “Does the Current Expected Credit Loss Approach Decrease the Procyclicality of Banks’ Lending?” SSRN 4110109.

Covas, Francisco, and W. Nelson (2018). “Current Expected Credit Loss: Lessons from 2007-2009.” Banking Policy Institute Working Paper, https://bpi.com/wp-content/uploads/2018/07/CECL-Lessons-2007-2009-WP-July-12-2018.pdf.

De Araujo, D. K. G., B. H. Cohen, and P. Pogliani (2021). “Bank Loan Loss Provisioning During the COVID Crisis,” https://www.bis.org/publ/qtrpdf/r_qt2103w.htm.

Degryse, H., and C. Huylebroek (2022). “Preventing a Banking Crisis: Fiscal Support and Loan Loss Provisions During the COVID-19 Pandemic,” SSRN 4032747.

DeRitis, C., and M. Zandi (2018) “Gauging CECL Cyclicality,” Moody’s Analytics Analysis Paper, https://www.economy.com/mark-zandi/documents/2018-12-03-Gauging-CECL-Cyclicality.pdf.

Financial Stability Forum (2009). “Report of the Financial Stability Forum on Addressing Procyclicality in the Financial System,” http://www.fsb.org/wp-content/uploads/r_0904a.pdf.

Frame, S., K. Gerardi, and P. S. Willen (2015). "The Failure of Supervisory Stress Testing: Fannie Mae, Freddie Mac, and OFHEO," Federal Reserve Bank of Boston Working Paper 15-4.

Gerardi, K., A. Lehnert, S. Sherlund, and P. Willen (2008). "Making Sense of the Subprime Crisis." Brookings Papers of Economic Activity (Fall 2008).

Loudis, Bert, and B. Ranish (2019). "CECL and the Credit Cycle," *Finance and Economics Discussion Series* 2019-061. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2019.061.

Loudis, B., S. Pechenik, B. Ranish, C. M. Vojtech, and H. Xu (2021). "New Accounting Framework Faces Its First Test: CECL During the Pandemic." *FEDS Notes* (December 03, 2021), https://www.federalreserve.gov/econres/notes/feds-notes/new-accounting-framework-faces-its-first-test-cecl-during-the-pandemic-20211203.htm.

McKinsey & Company (2022). "Model Risk Management 2.0 Evolves to Address Continued Uncertainty of Risk-Related Events," https://www.mckinsey.com/.

Pinello, A., and E. L. Puschaver (2020). "CECL Encounters a 'Perfect Storm,'" *The CPA Journal* 90(7/8), 20–28.

Pinello, A. S., and L. Puschaver (2022). "Implementing CECL During the Pandemic: Unexpected Consequences Revealed," *The CPA Journal* 92(1/2), 20–27.

Wall, L. D., (2020). "Banks' Accumulated Credit Losses in the First Quarter," https://www.atlantafed.org/cenfis/publications/notesfromthevault/05-banks-accumulated-credit-losses-in-the-first-quarter-2020-05-29.

Waller C. J. (2021). "A Hopeless and Imperative Endeavor: Lessons from the Pandemic for Economic Forecasters," speech at the Forecasters Club of New York (December 17), https://www.federalreserve.gov/newsevents/speech/waller20211217a.htm.