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How Did CECL Affect Bank Lending?*

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Abstract

Adoption of the current expected credit losses (CECL) methodology for loan loss provisioning significantly altered how banks recognize loan losses in their capital calculations. Because capital is a more costly funding source for banks, the accounting change affects banks' cost of funding loans. Using variation in the timing and effect of CECL implementation across firms and loan types, this paper finds that loan loss allowances have a similar causal effect on credit supply as capital requirements. Within our sample, the effect of CECL adoption on loan allowances reduced loan growth by approximately 77 basis points annually in the years following adoption. We find no significant effect of CECL on capital distributions.

JEL: G21 G28 M41 M48

Keywords: current expected credit losses (CECL) methodology; bank lending; loan loss provisioning

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1 Introduction

How banks measure possible loan losses affects the size and timing of earnings because loan loss provisions reduce earnings and, therefore, capital. Because capital is a costlier funding source for banks, changes to loan loss accounting could affect lending just as a change in capital requirements might. This paper uses a required change in loan loss accounting methods to explore the relationship between loan loss allowances and lending growth.

On January 1, 2020, most large banks in the United States were required to adopt the current expected credit losses (CECL) methodology for loan loss provisioning, and all remaining banks were required to adopt it three years later. Under CECL, banks need to establish allowances sufficient to cover expected losses over the entire loan contract horizon. In comparison, the previous incurred loss model (ILM) approach required allowances only for probable losses as of the reporting date. Consequently, under CECL, loss provisions are made earlier in a loan's life cycle, before signs of credit deterioration emerge, and the level of allowances is generally higher, depending on the loan characteristics. In addition, the CECL methodology requires provisions to reflect changes in expected future credit losses associated with the macroeconomy, leading to significant changes to provisions around turning points in the economic cycle. As a result, the effect of CECL is likely to depend on the economic environment as well. Therefore, our empirical approaches and conclusions carefully consider the economic disruption from the coronavirus disease 2019 (COVID-19) pandemic, which emerged shortly after CECL's adoption by the largest banks.

To analyze the effect of loan loss accounting on lending, we compare 2020 CECL adopters (early adopters) with 2023 adopters (late adopters) using public regulatory data between 2016:Q1 and 2024:Q2. These bank groups are different by construction: Large public companies are early adopters, and private, generally smaller companies, are late adopters. This paper trims the panel to drop the very large and small banks to create a sample of banks that are operationally more similar. We also exclude lending associated with the Small Business Administration's Paycheck Protection Program, introduced to support the pandemic economy. To further address concerns about potential confounding due to differential exposure to the pandemic disruptions, our approaches control for differences in local area employment conditions and exposure to regional macroeconomic trends.

To identify effects of CECL, we use variation in CECL adoption's impact over time, across firms, and between loan products. We also use multiple approaches including differences-in-differences, instrumental variables (IV), and synthetic controls to control for various potential sources of confounding. Our conclusions are drawn from consideration of these approaches and robustness tests. While other papers have studied the effect of CECL on lending, our range of empirical approaches is more comprehensive, and our preferred instrumental variable approach ties the causal loan loss allowance effect of CECL more directly to its effect on bank capital. In addition, this preferred approach uses variation in the impact of CECL at adoption on January 1, 2020, which occurred well before the severe disruption of COVID-19 was widely anticipated.[1]

Our analysis starts simple with a difference-in-differences approach to show that adoption of the CECL methodology has a different sized effect on allowances across the different loan types, both for early and late adopters. However, the estimated effect on loan growth and allowances do not consistently go in opposite directions, as might be expected given CECL's impact on capital. Because the evidence at the loan type level is weak, we use approaches that make use of additional sources of variation in CECL's effect on allowances.

Through use of IV based on the size of the adoption effect, we can directly assess the link between loan allowances and lending. Our preferred IV approach uses firms' day-one CECL adoption effect as a source of variation. This approach suggests that a one percentage point increase in allowance coverage–the ratio of loan loss allowances to loans–decreases lending by approximately 0.85 percent per quarter. Extrapolating from this effect and considering the 24 basis point effect of CECL adoption on allowance coverage within our sample of banks, CECL adoption resulted in a 77 basis point decline in annual loan growth. This decline is moderately significant relative to aggregate annual loan growth, which averaged about 6.4 percent in our sample of banks. In contrast, we

[1] For later CECL adopters, the adoption date of January 1, 2023 occurs after economic conditions had largely normalized.

find no statistically significant effect of allowances on banks' capital distributions in the form of common stock distributions or share repurchases. In combination, these estimates suggest that the shock to allowances is accommodated primarily by reduced lending.

For further evidence that regulatory capital constraints are the mechanism behind the measured effect, we test whether the lending response to allowances varies with the extent to which capital requirements are a constraint for the bank. We find that the effect of changes in allowances on loan growth is significantly stronger for the most capital constrained banks than it is for the least constrained, with the effect size decreasing by about one-third of the average for each standard deviation increase in excess capital.

We further test the robustness of our results to reasonable variations in the testing methodology, including a synthetic instrumental controls approach that is robust to the possibility that early CECL adoption and its impact are correlated with an observed trend. The magnitude of results varies somewhat, with stronger results when weighting by portfolio size and weaker results with synthetic controls, but the overall conclusion remains. Overall, our results highlight the influence that accounting changes can have on bank behavior and, consequently, on the broader economy.

2 Background on CECL

The Financial Accounting Standards Board issued the CECL methodology on June 16, 2016.[2] CECL went into effect as part of U.S. generally accepted accounting principles for fiscal years starting after December 15, 2019, for Securities and Exchange Commission (SEC) filers, with adoption required for private companies three years thereafter. Consequently, CECL was adopted on January 1, 2020 by most public U.S. banks and January 1, 2023 by the remaining U.S. banks. Given the many factors associated with the decision to go public or private, firms effectively had little ability to choose their adoption date in advance.

CECL replaced the incurred loss model (ILM) method, as ILM proved insufficiently responsive to

[2] See Accounting Standards Update 2016-13 at `https://storage.fasb.org/ASU_2016-13.pdf`.

the deterioration in economic conditions that occurred in the 2007–09 financial crisis. Specifically, allowances remained low under the ILM after the economy had already entered a recession and the market value of bank equity had declined significantly, suggesting that a forward-looking standard might more closely align the accounting value of capital with economic reality.

Under CECL, firms are required to forecast loan balances, charge-off rates, and recovery rates. While expectations for model sophistication vary with firm size, firms are expected to incorporate forward-looking information to a greater extent than under the ILM method. Allowances are intended to cover only "incurred" losses under the ILM but are meant to cover losses over the expected remaining lifetime of the loan under the CECL methodology.

The differing conceptual basis for allowances under CECL means that they tend to be larger in practice, particularly when economic conditions are deteriorating. As allowances grow, accounting and regulatory measures of capital decline. Thus, an increase in the allowances constrains a bank similarly to an increase in the regulatory capital requirement.[3] Furthermore, CECL's requirement to recognize losses over the expected remaining lifetime moves forward the timing of loss recognition in a way which disincentivizes lending when banks are particularly concerned about meeting capital requirements in the short run.

To help illustrate the differences between the CECL methodology and the ILM, some simple examples are provided. Figure 1 shows an example of a three-year loan that originated when the economic outlook is for steady growth over the life of the loan. During such a macroeconomic setting, suppose a bank expects a 5 percent loss. So, on day one ($t = 0$), the allowance coverage (loan loss allowance/loan amount) is 5 percent. Ultimately, in this example, the loan does not default. The modeled allowance shrinks over time as the probability of a loan defaulting shrinks as the loan matures and bad outcomes seem less likely to materialize. The allowance at the end of year three is zero. The graph on the right in figure 1 shows the same coverage ratio but under the ILM methodology. Because the loan never defaulted or even showed signs of deterioration, there

[3] Banks with allowances exceeding 1.25 percent of credit risk-weighted assets are allowed to deduct this excess from total risk-weighted assets, but this deduction offsets only a small portion of the effect of the reduction in regulatory capital associated with the allowances.

was never a loan loss allowance change.

Figure 1: Allowance Model Comparison: Good Economy, Good Loan

Assume a three-year loan. Economic forecast projects slow, steady growth. The loan does not show any signs of deterioration over the three years.

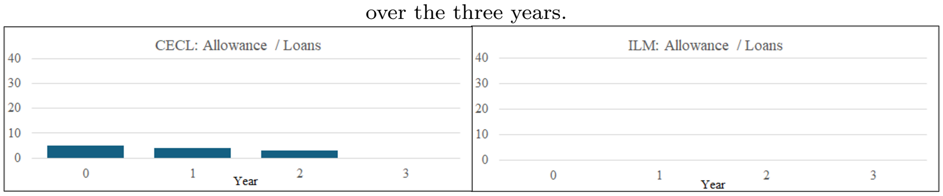
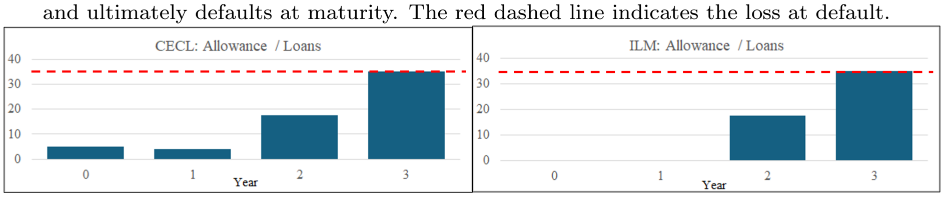


Figure 2 shows the same loan and economic outlook except now the loan has observable deterioration at the end of year two and ultimately defaults at the end of year three. The red dashed line indicates the actual loss. The allowance under CECL based on expectations for the first year is the same but would adjust higher when evidence of the possible default appears. For the ILM, the allowance would also increase in year two if the evidence made loan default probable. In this example, the same level is shown for CECL and the ILM. However, they could be different, depending on modeling assumptions and design. At default in year three, the same amount of provisions and reserves need to be booked to cover the loss under both methodologies.

Figure 2: Allowance Model Comparison: Good Economy, Bad Loan

Assume a three-year loan. Economic forecast projects slow, steady growth. The loan shows signs of deterioration in year two and ultimately defaults at maturity. The red dashed line indicates the loss at default.



Across these two examples, allowances build earlier under CECL than in the ILM. Relatedly, the average level of allowances under CECL is greater.

We turn now to the implementation of CECL by U.S. banks. Federal banking regulators passed a rule in early 2019 that would spread the adoption effect over three years.[4] This transition period was designed to give banks additional time for their capital plans to adjust.

However, the COVID-19 pandemic disrupted the economy shortly after most public banks adopted

[4] See 84 FR 4222 published February 14, 2019 (`https://www.govinfo.gov/content/pkg/FR-2019-02-14/pdf/2018-28281.pdf`).

CECL. Several emergency rulemakings responding to the pandemic affected the adoption and temporarily muted the effect of CECL on banks' regulatory capital. The Coronavirus Aid, Relief, and Economic Security (CARES) Act, signed into law on March 27, 2020, provided banking organizations the option of deferring CECL adoption until the end of the COVID-19 national emergency. Simultaneously, banking regulators issued an interim final rule that delayed the estimated effect of CECL on regulatory capital for three years, with a two-year transition period following.[5] Virtually all banks that chose to transition the capital effect of CECL opted for the more generous version under this emergency rulemaking. However, relatively few opted to delay CECL adoption under the CARES Act. Delaying would not provide firms much if any benefit to their regulatory capital given the more generous transition period put in place. In addition, as CECL had already come into effect, deferment would have imposed its own operational challenges associated with reverting back to old processes. Despite these challenges, other research suggests that those banks that did opt to delay CECL adoption tended to be better informed and more concerned about CECL's adoption effect.[6] Thus, by excluding these firms from our sample, as discussed in section 4, we are understating the extent to which banks responded to CECL adoption.

3 Related Literature

The allowance for loan losses is a contra-asset account. Therefore, it is effectively funding the loans that are expected to lose value or otherwise have reduced payments. Within the funding structure, capital is also designed to absorb losses because it is the residual claimant. There is no legal obligation to pay back holders of capital. The appropriate level of capital has been a subject of long-term debate and is outside the scope of this paper.[7] However, compared with other sources of bank funding, capital is generally more expensive, at least from the banks' perspective. By changing the requirement to build in an earlier loan loss buffer and possibly increasing funding costs, CECL could change lending behavior.

[5] See 85 FR 17723 published March 31, 2020 (`https://www.govinfo.gov/content/pkg/FR-2020-03-31/pdf/2020-06770.pdf`).

[6] Kim, Kim, Kleymenova and Li (2026) review SEC filings and find that the banks reporting an advance estimate of CECL's adoption effect were more likely to opt to delay adoption. Similarly, Bonaldi, Liang and Yang (2023) use analysis of SEC filings to conclude that banks that were more concerned about the negative effect of CECL were more likely to delay adoption.

[7] See, for example, Basel Committee on Banking Supervision (2010), Admati et al. (2013), and Baker and Wurgler (2015).

Previous research has documented the importance of bank capital requirements for credit supply in several different settings. All of these results are consistent with capital being a more expensive funding source. Across studies, the long-run elasticity of lending to capital requirements (cumulative percentage change in lending in response to a one percent change in capital requirements) is between -0.2 and -0.8, with much of the lending adjustment observed over the few years following the change in capital requirements. For example, several papers look at the adoption effects of capital requirements in Europe. Fraisse, Lé and Thesmar (2020) analyze bank responses to adopting the Basel II framework in supervisory data. They find that a 1 percentage point (or roughly 12 percent) increase in capital requirements reduces lending by 2.3 to 4.5 percent. Mésonnier and Monks (2015) estimate that banks forced to raise their core Tier 1 capital ratio by 1 percentage point following the European Banking Authority's 2011–12 capital exercise have annualized loan growth 1.2 percent lower than unconstrained banks. Gropp et al. (2018) study the same capital exercise and find that banks subject to the exercise increase their capital ratios by 1.9 percentage points and decrease risk-weighted assets by 16 percentage points relative to the control group. Behn, Haselmann and Wachtel (2016) use a quasi-experimental research design to explore how a sudden increase in a capital requirement affects lending. They find that capital increases of 0.5 percentage point are associated with a 2.1 to 3.9 percentage point decline in lending. Additional examples of empirical studies of regulatory capital and lending include Aiyar et al. (2014); Aiyar, Calomiris and Wieladek (2014); Bridges et al. (2014); and De Jonghe, Dewachter and Ongena (2020). The range of our point estimates for the impact of allowances on loan growth is consistent with this literature. For example, our preferred estimate equates to an estimated elasticity of lending to capital requirements of about -0.6.[8]

Other papers explore the relationship between capital and lending in a dynamic model. For example, Berrospide and Edge (2010) use a variety of methods to explore how bank capital influences lending and generally find modest impact. In particular, an increase in the capital ratio of 1 percentage point is associated with a long-run increase in annualized BHC loan growth that is only between

[8] Our estimated coefficient of -0.85 (table 4) implies a cumulative change in lending over three years of about -10 percent. A one percentage point increase in allowance coverage is equivalent to a 16 percent increase in capital requirements when assuming that average loan risk weights are 70 percent, 90 percent of the allowance impact is translated to capital, and capital requirements are 8 percent; $\frac{0.01\times0.9}{0.7\times0.08} = 0.16$. Therefore, a 16 percent increase in capital requirements is estimated as decreasing lending 10 percent; $\frac{-10}{16} = -0.6$

0.7 and 1.2 percentage points. This is an equilibrium effect: banks with higher capitalization rates tend to lend more in the next period. This is true even after trying to control for things like bank characteristics and the macroeconomic environment.[9] Carlson, Shan and Warusawitharana (2013) try to identify the relationship at the local level so as to better control for loan demand. They estimate that the elasticity of bank lending with respect to capital ratios is higher in crisis periods when capital ratios are relatively low. This suggests that the effect of capital ratio on bank lending is nonlinear. This is consistent with our results when we interact the adoption of CECL with how capital-constrained an individual firm is. Firms with tighter capital constraints have even less loan growth than other CECL adopters.

The first stage of our work closely relates to Covas and Dionis (2021), as well as Loudis et al. (2021). These papers explore the effects of CECL on allowances and growth of different types of loans. They find a significant effect of CECL on the allowances and growth of consumer loans, but no effect of CECL adoption on the growth rates of other forms of lending. Covas and Dionis (2021) argue that this non-result is expected as the emergency rulemakings offset the capital impact for other forms of lending, while Loudis et al. (2021) are hesitant to infer much from the impact on consumer lending. Our work expands materially on these earlier findings by also considering variability in firm-specific CECL effect, employing additional empirical strategies, and incorporating the post-pandemic experience of CECL late adopters.

Chen et al. (2025), Granja and Nagel (2025), and Yang (2025) also estimate the effect of CECL adoption on lending, but are more narrow in coverage than this paper. Yang (2025) focuses on residential mortgage lending, and finds a reduction in balance sheet lending in favor of securitization for banks adopting CECL. Granja and Nagel (2025) finds an effect of CECL on the pricing of consumer loans. Chen et al. (2025) find a significant effect of CECL on overall lending and possible downstream effect on employment in 2020. By focusing on that stress episode, they argue that the effects demonstrate that CECL has a procyclical effect. Several other studies explore the effect of CECL on lending procyclicality, but most are more hypothetical, using data before actual CECL

[9] Other related papers include Bernanke, Lown and Friedman (1991), Hancock and Wilcox (1993), and Gambacorta and Mistrulli (2004).

adoption.[10] In comparison to Chen et al. (2025), our work considers a longer time period and additional empirical methods to better identify the mechanism.

This paper is connected to the broader literature on CECL. For example, other papers study other effects of CECL adoption, including bank information production and financial reporting. Hu (2024) looks at the effect of CECL on small business lending and finds that banks reduce their lending more on businesses that are farther from physical branches. This result is consistent with theories about information acquisition. Adopting CECL is associated with higher information acquisition or production costs, making distant borrowers more expensive. Relatedly, Kim et al. (2026) show that banks adopting CECL have changes in their financial reporting and operations that are consistent with better information production.

This paper is also related to research that examines the lending effects of a similar accounting standard issued by the International Accounting Standards Board (IASB) on bank lending in other countries. In 2018, under International Financial Reporting Standards (IFRS) 9, firms using IASB standards needed to use an expected credit loss (ECL) model for valuing financial assets and liabilities. Ertan (2025) finds that banks that adopted IFRS 9 reduced lending to small and medium-sized enterprises by over 10 percent. However, the research explains these results as more due to banks' financial reporting concerns and implementation difficulties as opposed to simply higher loan loss allowances. Bojar and Olszak (2022) study publicly traded banks in Poland and do not find a direct effect of IFRS 9 on lending. However, there is a positive and significant relationship between IFRS 9 and capital, suggesting that banks with higher capital ratios were better able to extend more loans during the implementation period.

4 Data

Our data sample begins in 2016:Q1 and ends in 2024:Q2. As discussed in section 2, entities adopted CECL either following January 1, 2020 ("early adopters") or January 1, 2023 ("late adopters").

[10] See, for example, Cohen and Gerald A. Edwards (2017); Abad and Suarez (2018); Covas and Nelson (2018); Harris, Khan and Nissim (2018); Loudis and Ranish (2019); and Chae et al. (2021). Jia, Kanagaretnam and Zhang (2025) looks at the pro-cyclicality of loan loss provisions.

This time frame means our sample has four years of data before and after CECL enactment for the early adopters and six quarters of data following enactment by the late adopters.

Because this paper analyzes bank holding companies (BHCs) as well as standalone commercial banks that are not in a BHC, the data are a combination of Call Report (commercial bank) and FR Y-9C (BHC) data. Throughout this paper, we refer to all firms as "banks."

To ensure that changes in corporate structure, such as mergers, are not misinterpreted as large shocks, we aggregate balance sheets across entities so that they represent consistently consolidated banking businesses over time. Most commonly, one or more depository institutions have always been consolidated into the same holding company over our sample period. In this case, we include only the balance sheet for the holding company.[11] However, in the case of mergers that occur during our sample period, this means constructing historical "pseudo-banks" by retroactively consolidating the balance sheets of the entities that later merged.

In addition, we measure loan balances throughout our sample exclusive of loans issued through the Small Business Administration's Paycheck Protection Program (PPP).[12] PPP loans were forgivable and would ultimately be repaid by the government. Relatedly, PPP loans did not require allowances for credit losses and had no associated risk-based capital requirements. While the PPP was a significant source of aggregate loan growth in 2020, particularly for CECL late adopters, it would not have a clear connection with firms' capital management processes—and the channel by which it would have been affected is unclear. By excluding these loans, we remove their potentially distortionary effect from the analysis and match the practices of other researchers (e.g., Chen, Dou, Ryan and Zou (2025); Kim, Kim, Kleymenova and Li (2026)).

Our data sample is designed to focus on a set of banks that are relatively comparable in terms of their complexity and regulatory environment and for which a significant but not overwhelming share

[11] However, if the holding company is too small to meet the filing requirements for the FR Y-9C, we instead aggregate the balance sheets of the depository institutions, excluding any whose financials are already aggregated within another depository institution under that same holding company.

[12] In most cases, PPP loans were classified as commercial loans, but as noted below, we exclude some firms for which the attribution of PPP loans is unclear.

adopted CECL in January 2020. Toward this aim, we exclude banks with less than $1 billion or more than $100 billion in consolidated assets as of 2019:Q4. The largest banks are excluded because they are subject to heightened supervision and additional regulation, and almost all adopted CECL in 2020. As a result, they are not good controls against which to measure outcomes. Similarly, the smallest banks are largely privately held, and few were required to adopt CECL in 2020. In addition, for the smallest banks, the operational burden of CECL adoption and maintenance may represent a greater burden than the change in allowances. To simplify the analysis, from this set of 667 intermediate-sized banks, we also exclude 139 that adopted CECL in quarters other than 2020:Q1 or 2023:Q1.[13] From the remaining 528 firms, we exclude 6 for which lending is a relatively unimportant part of the business model.[14] Our remaining data filters are designed to address potential data quality and comparability issues.[15] Our final sample consists of 364 firms, accounting for 9,779 firm-quarters of data. We create a further panel of 45,574 firm-loan type-quarters using the six loan types for which the regulatory reports provide tracking of both allowances and loan balances: construction (CNSTR), commercial real estate (CRE), commercial (COM), residential real estate (RRE), credit cards (CARDS), and other consumer loans (OTHCONS).[16] We also winsorize variables with significant outliers (loan growth, delinquency measures) at the 1st and 99th percentiles.[17]

Table 1 summarizes the primary sample used in this paper, comparing the average values of the variables for the early adopters with those for the late adopters. As expected, the early adopters tend to be larger (see log assets). They also tend to have lower allowance coverage before CECL despite having similar credit quality measures (delinquency rates and nonaccrual rate). Reflecting that early adoption is primarily determined by whether the bank is public, early adopters have a

[13]This count includes products of significant mergers—i.e., where at least 10 percent of assets are from each firm—of early and late adopting CECL firms.

[14]Based on 2019:Q4 balance sheets, we exclude banks where loans are less than 25 percent of assets.

[15]Specifically, we exclude 52 banks reporting the effect of CECL adoption on allowances as exactly zero, as it is too difficult to distinguish reporting errors from instances where qualitative management buffers in allowances are adjusted to exactly offset what would otherwise be the effect of CECL adoption, In addition, we exclude 31 banks for which we are unable to construct measures of loan growth or allowance balances that are consistent over time and exclusive of PPP lending, and a final 75 banks for which we lack sufficient data on loan growth, leverage ratios, or year-end 2019 data.

[16]We exclude de minimus loan portfolios (where lagged balances are less than $10 million).

[17]Winsorizing growth outliers is justified by the prior that extremely large growth outcomes are unlikely to be materially driven by CECL.

much higher share repurchase rate, and somewhat higher average dividend rate–as a share of assets. However, both early and late adopters have similar loan portfolios (bottom six rows), with early adopters having a bit more exposure to commercial loans and a bit less exposure to RRE loans. Few firms within the sample have significant credit card exposure.[18] Notwithstanding this overall similarity in loan portfolios, early CECL adopters' allowances had a significantly higher adoption effect (0.38 versus 0.10 percent of loan balances). Finally, from the observation counts, we have more late (268) than early (96) adopting banks within the sample.

Table 1: Summary Statistics (Means), by CECL Adopter Type and Time Period

	Early Adopters			Late Adopters		
	2016–19	2020–22	2023–24	2016–19	2020–22	2023–24
Loan growth	2.18	1.86	0.96	1.99	2.33	1.69
Allowance coverage	1.18	1.73	1.58	1.28	1.45	1.37
Adoption effect		0.38				0.10
30-day delinq.	0.52	0.41	0.42	0.50	0.39	0.34
90-day delinq.	0.26	0.26	0.23	0.15	0.18	0.15
Nonaccrual	0.71	0.54	0.43	0.69	0.61	0.47
Log assets	16.42	16.67	16.75	14.61	14.98	15.11
Tier 1 leverage	10.31	9.70	9.94	10.47	10.04	10.34
Return on assets	1.12	1.17	1.22	1.03	1.15	1.00
Common dividends/assets (pp)	0.45	0.47	0.49	0.40	0.38	0.32
Share repurchases/assets (pp)	0.23	0.25	0.13	0.03	0.04	0.03
Share of loans (pp)						
Commercial	24.63	25.40	24.60	19.68	18.94	18.55
Commercial real estate	35.06	35.29	34.95	37.33	39.11	38.45
Construction	6.68	6.92	7.46	6.67	7.48	7.95
Residential real estate	23.81	22.74	23.63	29.72	29.06	29.64
Cards	3.22	3.36	3.32	1.26	1.42	1.37
Other consumer	6.60	6.29	6.03	5.34	3.99	4.04
Branch-weighted macroeconomic conditions						
Unemployment rate	4.21	5.45	3.80	3.98	5.17	3.65
Employment growth	1.25	0.34	1.25	1.15	0.29	1.26
Observations	1,525	1,140	566	3,387	2,088	1,073

Source: FR Y-9C, Call Reports, FFIEC branch data, and Bureau of Labor Statistics.

Table 2 provides the distribution of the variables within the early and late adopter subgroups: standard deviation, 5th percentile, and 95th percentile. There is significant overlap in the distribution

[18] Credit card exposures are concentrated in the very largest banks, which are not part of our sample.

of each variable between the two adoption groups, with the smallest early adopters smaller than the largest late adopters. The last two rows provide some evidence that early and late adopters also faced similar macroeconomic environments. Branch-weighted average unemployment rates and employment growth have similar distributions across the two groups. This is particularly important to check given the relationship between CECL, the economic environment, and general loan demand.

Figure A1 in the appendix shows that our sample is geographically representative of all banks, and that early and late adopter banks' branches have similar geographic distributions. The top U.S. map subtracts each state's share of branches across all banks from state's branch share within our sample. The most notable difference is that our sample has a lower share of branches in New York state, but our sample is broad enough that there is no particular regional concentration. The bottom map compares the average branch share, by state, of the early and late adopters. Most states are light red or blue, indicating that the share of bank branches between the compared groups are at most 2 percentage points different from each other. The differences across all states are not statistically significant; the p-value for the sum of absolute differences across states is 0.28.

5 Empirical Analysis

As shown in the simple loan example in the introduction, the CECL methodology was designed to build loan allowances earlier than under the ILM methodology, which has important implications for bank balance sheets and capital. As a contra-asset account, loan allowances offset loans on the balance sheet, effectively funding a portion of the loan portfolio. Without the credit loss provisions that build these allowances, more earnings would have been retained, increasing capital. For these reasons, the change to the credit loss accounting is comparable to an increase in required capital. Within our sample, the impact of the increase in allowances at adoption was equivalent to a 2.6 percent increase in capital.[19] As established in the literature (see section 3), higher capital

[19] Specifically, the adoption effect of CECL on capital of banks in our sample was 2.6 percent of their aggregate tier 1 capital.

Table 2: Summary Statistics (Distributions), by CECL Adopter Type

	Early Adopters			Late Adopters		
	StDev	5th	95th	StDev	5th	95th
Loan growth	3.75	-3.16	8.43	3.28	-2.30	7.40
Allowance coverage	1.63	0.55	2.76	1.16	0.58	2.37
Adoption effect	0.79	-0.05	1.33	0.48	-0.19	0.38
30-day delinq	0.59	0.05	1.79	0.57	0.01	1.46
90-day delinq	0.68	0.00	1.42	0.66	0.00	0.55
Nonaccrual	0.56	0.05	1.54	0.62	0.03	1.90
Log assets	0.90	15.23	18.08	0.75	13.96	16.36
Tier 1 leverage	1.81	7.79	13.69	2.61	7.57	14.96
ROA	0.71	0.50	2.09	0.64	0.36	1.95
Common dividends/assets (pp)	0.59	0.00	0.81	0.49	0.00	1.25
Share repurchases/assets (pp)	0.38	0.00	0.89	0.11	0.00	0.23
Share of loans (pp)						
Commercial	15.60	2.12	55.97	13.60	0.63	44.62
Commercial real estate	15.24	0.00	60.08	16.97	4.04	66.06
Construction	6.12	0.00	15.79	5.31	0.00	16.60
Residential real estate	15.25	0.53	49.97	20.33	3.67	70.31
Credit cards	16.63	0.00	3.56	9.62	0.00	0.79
Other consumer	12.02	0.01	22.87	11.03	0.02	19.43
Branch-weighted macroeconomic conditions						
Unemployment rate	1.82	2.90	8.27	1.74	2.51	7.43
Employment growth	3.53	-6.30	5.55	3.41	-5.78	5.47

Source: FR Y-9C, Call Reports, FFIEC branch data, and Bureau of Labor Statistics.

requirements increase a bank's cost of funding, potentially reducing loan growth.[20]

In summary, the expected relationships are as follows: (1) CECL will increase a bank's loan allowance coverage (loan loss allowance / total loans), and (2) the increase in allowance coverage will raise funding costs, which will decrease loan growth.

5.1 CECL Effect, by Loan Type

We start our analysis by applying a well-established difference-in-differences methodology, measuring the change in loan growth and allowance coverage around CECL adoption. We perform this

[20]The social cost of capital requirements, which accounts for transfers and externalities associated with bank failures, is different.

analysis separately for each of the six loan loan types p for which the regulatory reports provide allowance and loan balance data. We also include separate dummies ($OnCECL$) to indicate the bank-time observations where the CECL methodology is in effect for early and late adopting banks. This approach allows the effect of CECL to be different for these two cohorts. We include a set of bank-level variables as additional controls ($BankControls$). The bank-level control variables include three asset quality controls, three bank characteristic variables, and additional controls for local macroeconomic conditions–which may affect loan demand. Asset quality is measured by delinquency rates at 30-day, 90-day, and nonaccrual frequencies. The three bank characteristic variables are lagged by one period to avoid endogeneity issues and include log assets, leverage ratio, and return on assets to control for size, solvency, and profitability. The macroeconomic controls include branch-weighted average unemployment rates and employment growth over the previous year.[21] In addition, the shares of each banks' branches in each of nine regional Census Divisions ($Region$) in every quarter is included to control for regional economic trends. Our regression corresponds to equation (1)

$$\begin{aligned} Y_{p,i,t} &= \beta_p^{early}\,\mathrm{OnCECL}_{i,t} + \beta_p^{late}\,\mathrm{OnCECL}_{i,t} \\ &\quad + \Gamma_p\,\mathrm{BankControls}_{i,t-1} + \Lambda_{p,t}\,\mathrm{Region}_{i,t-1} + \delta_{p,t} + \theta_{p,i} + \varepsilon_{p,i,t} \end{aligned} \tag{1}$$

where $Y_{p,i,t}$ is allowance coverage or loan growth at the bank-loan type level. The β's are the coefficients of interest in this specification and capture average differences that emerge between the bank groups from the time of CECL adoption.

Before running this regression, we first test an identifying assumption—that loan growth and allowance follow parallel trends for early and late adopters before early CECL adoption (2020). To test this assumption, we replace the "on CECL" dummies and quarterly fixed effects with an interaction of all quarterly dummies with an early CECL adopter dummy. Next, we run a Wald test of the joint statistical significance of the 16 quarterly interaction terms occurring in the years before early CECL adoption, 2016 to 2019. A low joint significance is a sign that the parallel trends

[21] We weight county level data from the Bureau of Labor Statistics by the share of each banks' branches in that county.

assumption cannot be rejected, and causal claims in the difference-in-difference regression might be valid. The p-values for this test are provided in table 3, and the full set of interaction terms are plotted in the appendix (figures A2 and A3).

Table 3: p-values for Joint Significance of 2016–19 Early Adopter X Quarter Interaction Terms

	Allowance / Loans	Loan Growth
Commercial	0.39	0.21
Commercial real estate	0.03	0.25
Construction	0.63	0.65
Residential real estate	0.62	0.54
Cards	0.81	0.69
Other consumer	0.13	0.28

None of the loan types have pre-adoption loan growth trends that are statistically significantly different for early and late CECL adopters. The pre-adoption allowance trend is only statistically significantly different for CRE loans, but the difference in trends is economically small and appears to result from a gradual decline in the relative CRE allowances of early CECL adopters leading up to 2020. (See appendix figure A3.) The consequence of this deviation from parallel trends could be a slight underestimate of the effect of CECL on CRE allowances in 2020.

Another identifying assumption for the difference-in-differences methodology is that the treatment is applied quasi-exogenously, or orthogonal to other reasons that would predict a different change in allowance or loan growth between the early and late CECL adopters. Treatment, or early adoption of CECL, was primarily based on the definition of an SEC filer. Firms choose to be filers, so the treatment is not random. However, SEC filers and non-filers appear broadly similar apart from average size differences (see tables 1 and 2), and there are no other proximate changes related to SEC filing status that would affect the outcomes we measure. Thus, it may be reasonable to consider SEC filing status, and thus the timing of CECL adoption as as quasi-exogenous, or as good as random for the purposes of identifying CECL's effect.

Of course, the early adoption of CECL coincides with the onset of the COVID-19 pandemic–

which undoubtedly had an effect on allowances and loan growth. Our identification approach only requires that the pandemic's effect on individual banks was orthogonal to whether or not they were early adopters. However, the presence of the pandemic does change the interpretation of the CECL effect we measure. We estimate the effect of CECL on allowances and loan growth under conditions characterized by significant economic uncertainty and expected, though largely unrealized, economic stress.

As the identification considerations are generally satisfied, we proceed to estimate regression equation (1) by ordinary least squares (OLS), using standard errors robust to clustering within banks. The coefficients representing CECL's effect on each loan type are presented as data points in figure 3, with estimates for the early adopters (i.e., β_p^{early}) in the top plot and estimates for the late adopters (i.e., β_p^{late}) in the bottom plot. The x-axis is the estimate from the allowance coverage regression, and the y-axis is the estimate from the loan growth regression. The dashed gray lines represent statistical 95 percent confidence intervals for these estimates.

For the 2020 adoption plot, all six dots are to the right of the zero line for the x-axis, suggesting that, on average, allowances increased for CECL adopters after the rule adoption. The result is statistically significant for three loan types: RRE, CRE, and construction. Five of the dots are below the zero line for the y-axis, suggesting that, on average, loan growth was negative after CECL for adopters. However, this result is not statistically significant for any of the loan types.

For the 2023 adoption plot, four dots are to the right of the zero line for the x-axis, suggesting that, on average, allowances increased for those loan types after the rule adoption. But the result is only statistically significant for construction loans. Three of the dots are below the zero line for the y-axis, and none are statistically significant. This result suggests that the later CECL adoption had minimal effect on average loan growth.

This loan type-level analysis does not present a perfectly consistent story of CECL affecting loan growth through an effect on allowances.[22] For example, in the 2020 adoption, construction loans

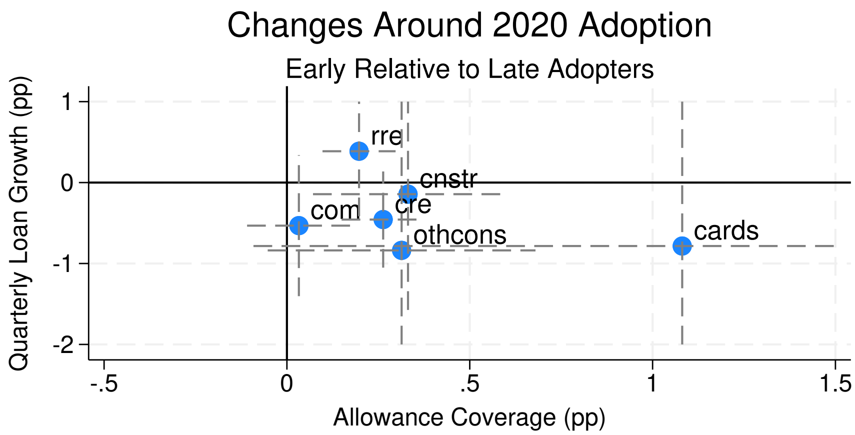
[22] More details of these tests and additional results are available in the appendix. Tables A2 and A3 show regression

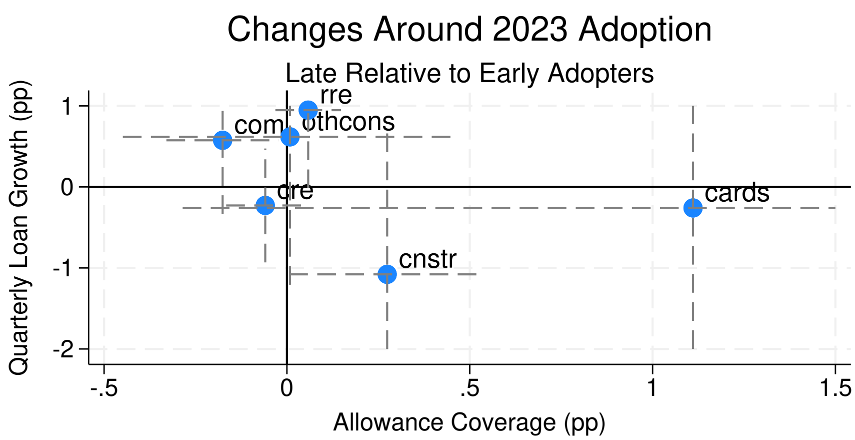
Figure 3: Difference-in-Differences Estimates

These figures plot the results of running the following regression:

$$Y_{p,i,t} \quad = \quad \beta_p^{early}\,\text{OnCECL}_{i,t} + \beta_p^{late}\,\text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \delta_{p,t} + \theta_{p,i} + \varepsilon_{p,i,t},$$

where Y is loan growth or allowance coverage, and $\text{BankControls}_{i,t-1}$ include three asset quality controls, three bank characteristic variables, and macroeconomic controls. In the top figure, the β_p^{early} values are plotted with the dots for each loan type p. The bottom figure plots β_p^{late}. The dashed gray lines represent statistical 95 percent confidence intervals for these coefficient estimates. cards = credit card loans, com = commercial and industrial loans, cre = commercial real estate loans, cnstr = construction loans, and othcons = other consumer loans.
Source: Call Report, FR Y-9C, and author calculations.





have a large allowance effect for early and late adopters but a statistically zero effect on loan growth. RRE loans have a positive loan growth rate for late adopters but statistically zero effect on allowance coverage. Only commercial lending for late adopters is consistent with a loan allowance mechanism and in the opposite direction. Allowances decreased, and lending increased. However, the evidence

details: coefficients and standard errors.

across loan types is suggestive: Five of the coefficient estimates are in the bottom-right quadrant for 2020 adoption. The dots in the 2023 adoption plot are near the top-left and bottom-right quadrants. The weakness of the difference-in-differences results is primarily because loan composition is not strongly correlated with effect of CECL on allowances. This is why our preferred specification will use information about the firm-specific effect of CECL adoption on allowances.

5.2 Allowance-Driven Lending Effect

We turn next to specifications that leverage heterogeneity in the CECL methodology's effect on allowances to test for evidence of an allowance-driven effect of CECL on loan growth. By restricting the impact of CECL to operate through its effect on allowances, identification is cleaner as we restrict the potential sources of confounding to those differences between banks that also relate to the effect of CECL on allowances. In addition, this approach also allows for a direct comparison to studies of the effect of changes in capital requirements on lending.

In our specifications, we regress loan growth on allowance coverage, and use instruments that capture the effect of CECL on allowance coverage. We use two instrumental variable (IV) strategies: one based on variation in CECL effect across banks and one based on variation in CECL effect across loan types. In each, we still expect an increase in allowance coverage to have a negative effect on loan growth.

IV Strategy 1: CECL's bank-specific adoption effect

The first instrumentation strategy identifies effects from heterogeneity in the firm-specific effect of CECL adoption on allowances.[23] Specifically, a dummy "OnCECL," indicating when the given firms' allowances are calculated under CECL, interacts with the bank-specific effect of CECL adoption on allowances ("AdoptionEffect"). The adoption effect is calculated as the increase in allowances due to CECL on day one divided by total loans.

[23] Because the adoption effect of CECL is not reported for each loan type, a bank×loan type effect is not possible.

The bank level testing specification is

$$
\begin{aligned}
\text{LoanGr}_{i,t} &= \beta\,\text{AllowanceCov}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\
&\quad + \Phi_t \text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \qquad (2) \\
\text{AllowanceCov}_{i,t} &= \alpha \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\
&\quad + \Phi_t^* \text{LoanShare}_{i,t} + \theta_i^* + \varepsilon_{i,t}^*, \qquad (3)
\end{aligned}
$$

where the bank-level control variables are defined as before and include three asset quality controls, three bank characteristic variables, and the macroeconomic controls. The additional control $\text{LoanShare}_{i,t}$ is a vector of five variables that are equal to loan shares of five of the six loan types. We allow the effect of loan composition on bank level allowances and loan growth to be time-varying to account for differences in trends across the different loan types.

IV Strategy 2: CECL's effect on allowances by loan type

The second instrument uses the $OnCECL_{i,t}$ dummy directly. Because CECL is a forward-looking methodology and, importantly, reflects expected credit losses through loan contracts' maturity, the average increase of allowance coverage when CECL is adopted will likely vary by loan type. This testing strategy treats the heterogeneity in CECL's effect across loan types along with the differences in CECL adoption dates as quasi-exogenous changes in allowances with which to assess the effect on loan growth.

The testing specification is

$$
\begin{aligned}
\text{LoanGr}_{p,i,t} &= \beta\,\text{AllowanceCov}_{p,i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\
&\quad + \delta_{p,t} + \theta_i + \varepsilon_{p,i,t} \qquad (4) \\
\text{AllowanceCov}_{p,i,t} &= \alpha_p\,\text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\
&\quad + \delta_{p,t}^* + \theta_i^* + \varepsilon_{p,i,t}^*, \qquad (5)
\end{aligned}
$$

where the control variables are defined as before and p represents the loan type.

The two instrumental variable strategies are complementary. The bank-specific effect of CECL adoption is a significant source of variability in allowances beyond differences in the composition of loan portfolios across banks. Specifically, the distribution of banks' loans across the six types explains only a small part of the variability of the bank-level adoption effect.[24] While our data do not provide the adoption effect of CECL on allowances at the bank-loan type level, we similarly note that the change in bank-loan type allowances around CECL adoption is statistically significantly predicted by the loan type even conditional on the bank-level adoption effect.

By representing different sources of variation, the two strategies have different vulnerabilities to potential sources of endogeneity. For example, if it were the case that a type of bank adopted CECL in a particularly conservative way and also grew more slowly for unrelated reasons, this would challenge the exogeneity of the instruments in our first strategy but would not affect our second strategy, which does not use this bank-specific variation.

Table 4 summarizes the results of the OLS and IV regressions specified above in equations (2) through (5). All coefficients of interest (β) have the expected negative sign; higher allowances are associated with lower subsequent loan growth. Also, the OLS coefficients are larger in magnitude than the IV coefficients, consistent with the expected endogeneity bias. Specifically, the financial health of a bank's customer base is likely to drive allowances for credit losses and credit extension in opposite directions.

The bank-level instrumental variables regression finds a statistically and economically significant effect of allowances on loan growth. With respect to economic significance, a coefficient of -0.85 suggests that CECL adoption decreased annual loan growth by approximately 77 basis points for the average bank in our sample.[25] This is moderately significant relative to aggregate annual loan growth of banks in our sample of about 6.4 percent. At the same time, as noted above, CECL adoption reduced capital by about 2.6 percent across the aggregate of banks in our sample. Our

[24] For example, a regression of the bank level adoption effect on allowances of early CECL adopters on $LoanShare_{i,2019Q4}$ has an associated R-squared of only 0.019.

[25] Allowance coverage increased, on average, 24 basis points with CECL adoption. Multiplied by the coefficient of -0.85 and annualized, this estimated treatment effect is $(1 - 0.85 * 24 \text{ basis points})^4 - 1 = 77$ basis points.

Table 4: OLS and IV Regression Results

This table shows the results of using the following specifications. The coefficient on allowance coverage (β) for the loan growth specification is reported. Results from the first set of equations are reported in columns (1) and (2) and the second set in columns (3) and (4).

$$\begin{aligned}
\text{LoanGr}_{i,t} &= \beta\,\text{AllowanceCov}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi_t\text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \\
\text{AllowanceCov}_{i,t} &= \alpha\text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\
&\quad + \Phi^*_t\text{LoanShare}_{i,t} + \theta^*_i + \varepsilon^*_{i,t},
\end{aligned}$$

$$\begin{aligned}
\text{LoanGr}_{p,i,t} &= \beta\,\text{AllowanceCov}_{p,i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \delta_{p,t} + \theta_i + \varepsilon_{p,i,t} \\
\text{AllowanceCov}_{p,i,t} &= \alpha_p\,\text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \delta^*_{p,t} + \theta^*_i + \varepsilon^*_{p,i,t},
\end{aligned}$$

$\text{BankControls}_{i,t-1}$ include three asset quality controls, three bank characteristic variables, and macroeconomic controls. Asset quality is measured by delinquency rates at 30-day, 90-day, and nonaccrual frequencies. The three bank characteristic variables are lagged by one period to avoid endogeneity issues and include log assets, leverage ratio, and return on assets to control for size, solvency, and profitability. $\Phi^*_t\text{LoanShare}_{i,t}$ is a vector of five variables that are equal to loan shares of five of the six loan types, and $\text{OnCECL}_{i,t}$ is a dummy variable set to one after CECL adoption by bank i.

	Bank Level		Loan Type Level	
	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
Allowance Coverage	-1.147***	-0.851*	-0.270***	-0.072
	(0.251)	(0.443)	(0.080)	(0.356)
Loan Type × Quarter FE			Y	Y
Loan Type Share × Quarter Effects	Y	Y		
Regional Exposure × Quarter Effects	Y	Y	Y	Y
Bank FE and Controls	Y	Y	Y	Y
First-Stage F		78.812		5.309
Observations	9771	9771	45574	45574

Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

estimates therefore suggest an impact on annual lending growth that is about 0.3 times as large as the percentage impact on capital requirements, which is within the broad range reported in the literature summarized in section 3.

In contrast to estimates using the bank-level effect of CECL, the coefficient from the loan type effect strategy is not statistically different from zero. However, we would caution about drawing strong conclusions from the loan type level estimates given the apparent weakness of the instruments.[26] The overall weakness of the instrument likely results from the relatively limited number of firms with the types of loans (e.g., cards and other retail) for which the average impact is very different from the average across all loans. In addition, depending on the composition and expertise in types of loans, individual banks may choose to meet stricter overall requirements in part by reducing credit availability even for loan types where the changes in treatment are minimal.[27] If so, this would also help to explain the smaller magnitude of coefficients at the loan type level.

5.3 Extensions

In this section, we extend our analysis in search of a richer set of results to better understand the mechanism. We look for evidence of an anticipatory effect, and test the persistence of the response to CECL adoption. We test whether more capital constrained banks behave differently. Lastly, we test whether CECL adoption affects banks' capital distributions in addition to their lending.

5.3.1 Timing

First, we relax our assumption around when firms respond to the effect of CECL on allowances. Thus far, our specifications assume that the effect of CECL on loan growth occurs only after adoption and is constant (per unit of effect on allowances) over the observed post-adoption period. There is some reason for skepticism regarding these assumptions. Given that the CECL methodology and adoption requirements were known well beforehand, it is reasonable to expect that most banks knew the likely effect of CECL before adoption. As it may be costly for banks to quickly change

[26] Specifically, the Stock-Watson first-stage F statistic is less than 10. Results of the first-stage regression are reported in the appendix in table A4. Consistent with the difference-in-differences results, the relationships between loan type and allowance coverage are stronger for construction, RRE, and credit cards.

[27] This might happen, for example, if it is very difficult or costly for banks to quickly carry out the full warranted margin of adjustment through only portfolios with the most significant effect of CECL.

their loan exposures, we might expect that banks' lending decisions prior to CECL adoption might reflect the anticipated effect of CECL on allowances. Relatedly, as the credit supply effect of CECL becomes fully reflected across the bank's business and loan types over time, we might expect the effect of CECL adoption on loan growth to fade to zero.

To assess the timing of CECL's effect on lending, we run a panel regression of loan growth on each banks' adoption effect, interacted with a dummy for the time-to-adoption τ. As shown in equation (6), the regression specification includes bank and quarter fixed effects as well. The β_{-1} term is removed from the equation, so that the impact of the adoption effect on lending is measured relative to the year prior to CECL's adoption by the bank. As this regression is run over data from 2016 through 2023, effects more than four years prior to adoption are identified from only late CECL adopters, and effects following the year of adoption are identified only from early CECL adopters.

$$\text{LoanGr}_{i,t} \quad = \quad \beta_{\tau,\tau\neq-1}\,\text{AdoptionEffect}_i + \delta_t + \theta_i + \varepsilon_{i,t} \tag{6}$$

The coefficients β_τ from this regression are plotted in figure 4, with $\beta_{-1} = 0$ by construction. The lighter lines bounding the coefficients represent the 95 percent confidence interval.

In Figure 4, the relationship between CECL adoption effect and loan growth is stable in the years prior to CECL adoption. There is no evidence of the downward trend that one might expect to result from an anticipatory effect. Following CECL adoption, this relationship remains stable and negative. While this could suggest a longer lasting effect of CECL on loan growth, limited statistical power precludes ruling out a moderate or asymptotic decline in CECL's effect on growth over time.

5.3.2 Interaction with Capital Constraints

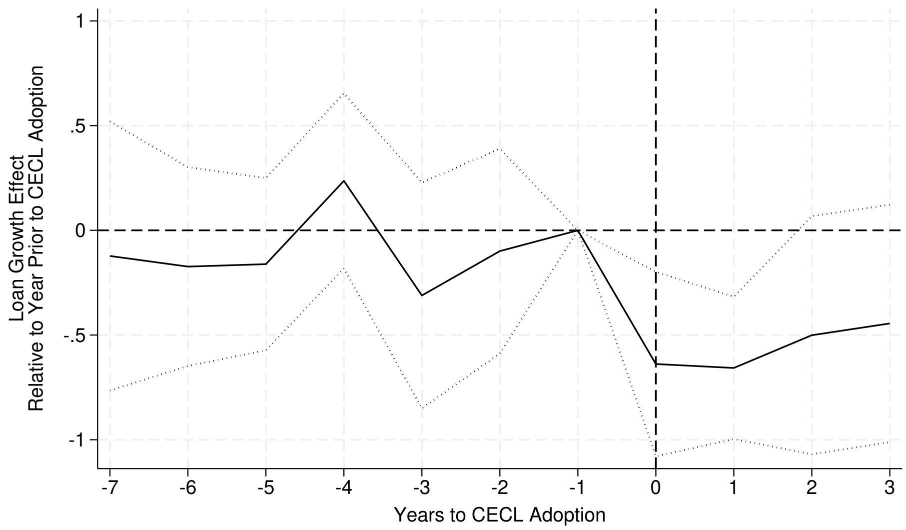
This paper generally tests the effect of CECL based on its effect on bank capital. In this section, we test whether the effect of CECL on loan growth is stronger at banks where the level of capital is closer to requirements and potentially a greater constraint on growth. We measure the bindingness

Figure 4: Relationship of Loan Growth and CECL Adoption Effect, by Time to Adoption

The coefficients β_τ from the following regression are plotted:

$$\text{LoanGr}_{i,t} \quad = \quad \beta_{\tau,\tau\neq-1}\,\text{AdoptionEffect}_i + \delta_t + \theta_i + \varepsilon_{i,t}.$$

Data sample covers the years 2016 through 2023.



of the constraint in two ways. As a simple approach, we use the minimum tier 1 leverage ratio of each bank over the period 2016 through 2019, prior to any CECL adoption.[28] As a more refined but complex alternative, we measure the ratio of each firms' common equity tier 1 capital relative to requirements, and do the same for tier 1 and total capital measures. We then take the minimum of these ratios across the three definitions of capital, and across the period 2016 through 2019 and refer to this as "excess capital."

Then, we interact leverage and excess capital-based bindingness within our more-robust bank level IV specification (equation 2) in two ways. First, we find the median of each measure, and define dummies MoreConstrained (and LessConstrained) which equal one for banks that are more (and less) constrained than the median bank. The estimation equations with this approach are as follows,

[28]The results are not substantively affected if we instead use the years 2019 through 2022 to measure the bindingness of capital constraints for 2023 CECL adopters.

where the controls are defined as previously:

$$\begin{aligned}
\text{LoanGr}_{i,t} &= \beta_1\,\text{AllowanceCov}_{i,t} \times \text{MoreConstrained}_i + \beta_2\,\text{AllowanceCov}_{i,t} \times \text{LessConstrained}_i \\
&\quad +\Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi_t \text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \\
\text{AllowanceCov}_{i,t} &= (\alpha_0 \text{MoreConstrained}_i + \alpha_1 \text{LessConstrained}_i) \times \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} \\
&\quad +\Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi^*_t \text{LoanShare}_{i,t} + \theta^*_i + \varepsilon^*_{i,t},
\end{aligned}$$

Second, we normalize each ratio measure so that it has mean zero and standard deviation of one, and then interact this variable, Capital_i, with allowance coverage within the regression equation. The coefficient on allowance coverage is then interpreted as the effect of allowances on loan growth for a firm with average capital constraints, while the coefficient on the interaction indicates how the strength of that effect changes with each standard deviation in the capital constraint. The estimation equations under this second approach are:

$$\begin{aligned}
\text{LoanGr}_{i,t} &= \beta_1\,\text{AllowanceCov}_{i,t} + \beta_2\,\text{AllowanceCov}_{i,t} \times \text{Capital}_i \\
&\quad +\Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi_t \text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \\
\text{AllowanceCov}_{it} &= \alpha_0 \text{Capital}_i \times \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} \\
&\quad +\Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi^*_t \text{LoanShare}_{i,t} + \theta^*_i + \varepsilon^*_{i,t}
\end{aligned}$$

Table 5 reports the coefficients of interest (β_1 and β_2) from the second-stage regressions above. Columns (1) and (2) show the effect of allowances on loan growth for the more and less constrained banks using the two measures of capital constraint bindingness. Under either measure, the CECL effect on allowances appears to slow loan growth more for firms with tighter capital constraints, although the results for more and less constrained banks are only statistically significantly different from each other when using the more complex capital constraint measure.

Columns (3) and (4) provide results using the normalized measure of capital constraint bindingness. As expected, the coefficient on allowance coverage is negative, and the coefficient on the interaction term is positive; both are statistically significant. Given the normalization, this means that a bank

Table 5: IV Regression Results for More and Less Capital Constrained Banks

The table below presents the β coefficients from the first (columns 1 and 2) and second (columns 3 and 4) set of loan growth regression equations below. We measure capital constraints (MoreConstrained, LessConstrained, and Capital) with leverage ratios (columns 1 and 3) and excess capital (columns 2 and 4). Capital in the second set of equations is normalized to mean 0 and standard deviation of 1. See table 4 for a description of the other control variables.

$$
\begin{aligned}
\text{LoanGr}_{i,t} &= \beta_1 \text{ AllowanceCov}_{i,t} \times \text{MoreConstrained}_i + \beta_2 \text{ AllowanceCov}_{i,t} \times \text{LessConstrained}_i \\
&\quad + \Gamma_p \text{ BankControls}_{i,t-1} + \Lambda_{p,t} \text{ Region}_{i,t-1} + \Phi_t \text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \\
\text{AllowanceCov}_{i,t} &= (\alpha_0 \text{MoreConstrained}_i + \alpha_1 \text{LessConstrained}_i) \times \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} \\
&\quad + \Gamma_p \text{ BankControls}_{i,t-1} + \Lambda_{p,t} \text{ Region}_{i,t-1} + \Phi_t^* \text{LoanShare}_{i,t} + \theta_i^* + \varepsilon_{i,t}^*
\end{aligned}
$$

$$
\begin{aligned}
\text{LoanGr}_{i,t} &= \beta_1 \text{ AllowanceCov}_{i,t} + \beta_2 \text{ AllowanceCov}_{i,t} \times \text{Capital}_i \\
&\quad + \Gamma_p \text{ BankControls}_{i,t-1} + \Lambda_{p,t} \text{ Region}_{i,t-1} + \Phi_t \text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \\
\text{AllowanceCov}_{it} &= \alpha_0 \text{Capital}_i \times \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} \\
&\quad + \Gamma_p \text{ BankControls}_{i,t-1} + \Lambda_{p,t} \text{ Region}_{i,t-1} + \Phi_t^* \text{LoanShare}_{i,t} + \theta_i^* + \varepsilon_{i,t}^*
\end{aligned}
$$

	Sample Split at Median by		Interaction with Normalized	
	Leverage Ratio	Excess Capital	Leverage Ratio	Excess Capital
	(1)	(2)	(3)	(4)
Allowance Coverage			-1.380***	-1.207***
			(0.324)	(0.265)
× More Constrained	-1.200*	-1.498***		
	(0.623)	(0.242)		
× Less Constrained	-0.791*	-0.148		
	(0.435)	(0.496)		
× Capital			0.341***	0.450***
			(0.100)	(0.109)
Allowance Coverage			-1.440***	-1.232***
			(0.338)	(0.277)
× More Constrained	-1.333*	-1.510***		
	(0.692)	(0.261)		
× Less Constrained	-0.799*	-0.167		
	(0.449)	(0.521)		
× Capital			0.351***	0.445***
			(0.109)	(0.119)
Loan Share × Quarter Effects	Y	Y	Y	Y
Bank FE and Controls	Y	Y	Y	Y
Observations	9676	9771	9676	9771

Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

would need a lot of excess capital for CECL to not have an effect on lending. It takes about 3 standard deviations above the mean capital measure to offset the allowance coverage effect on loan growth.[29]

5.3.3 Capital Distributions

Banks face strong incentives to meet regulatory capital requirements, and possibly market expectations around maintaining a safe buffer of capital above them. To the extent that increases in allowances have little affect on lending quantities, which could theoretically be true,[30] then the bank would need to reduce its capital distributions to maintain regulatory capital ratios. Conversely, absence of evidence that capital distributions are affected by changes in allowances provides indirect evidence that the effect on lending is economically significant.

In this section, we test the impact of CECL on capital distributions, considering common stock dividends and stock repurchases. We focus on these measures of capital distributions as they reflect the least costly margin of adjustment.[31] Floyd, Li and Skinner (2015) show that banks have a higher and more stable propensity to pay dividends than other industrial firms. Fahlenbrach, Ko and Stulz (2024) find that banks have lower payouts in times of high regulation uncertainty. As a result, we expect that if there is any capital distribution reaction to CECL, it will most likely come in the form of lower repurchases.

Figure 5 plots average distributions scaled by assets by adoption cohort. Repurchases are only plotted for the early adopters because late CECL adopters are overwhelming privately owned banks with very limited repurchase activity. All distributions dip in 2020, likely driven by the pandemic. The increase in economic uncertainty could make capital distributions less appealing for banks.[32]

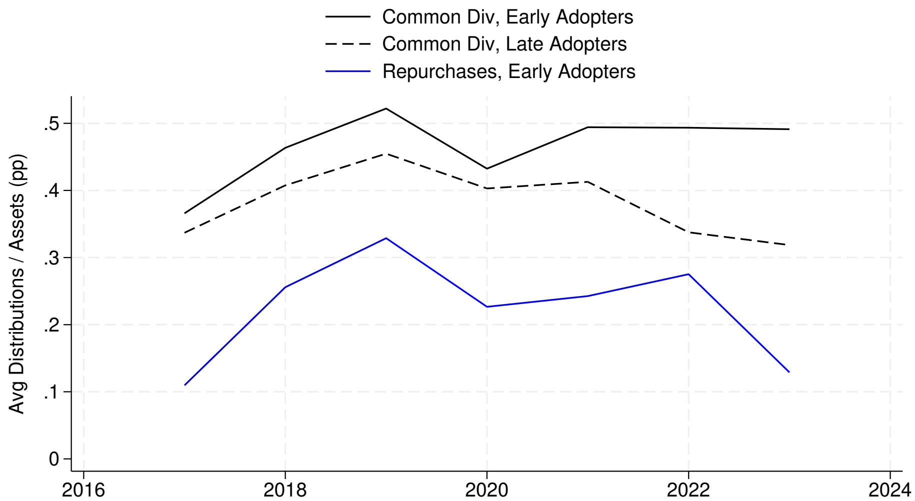
[29] For column (3), $-1.380/0.341 = 4.0$. For column (4), $-1.207/0.450 = 2.7$.

[30] For example, due to local market power, a bank could price some loan product above its marginal cost. In this event, it may be unprofitable to reduce lending even if funding costs increase.

[31] Alternative distributions include preferred stock dividends and share issuances.

[32] The Federal Reserve Board placed restrictions on repurchases for the stress tested banks. These firms are not in our sample, but such policies likely make it reputationally easier for the smaller firms to decrease distributions.

Figure 5: Capital Distributions from Early and Late CECL Adopters



To establish causality with CECL adoption, we turn to our preferred IV specification for the analysis:

$$\begin{aligned} \text{Distribution}_{i,t} &= \beta\,\text{AllowanceCov}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\ &\quad + \Phi_t \text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \qquad (7) \\ \text{AllowanceCov}_{i,t} &= \alpha \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\ &\quad + \Phi^*_t \text{LoanShare}_{i,t} + \theta^*_i + \varepsilon^*_{i,t}, \qquad (8) \end{aligned}$$

where the control variables are defined as before and include asset quality controls, bank and loan characteristic variables, and the macroeconomic controls. However, these regressions are run on annual data as distributions data are very lumpy, with strong seasonal patterns for some firms. For example, some banks have quarterly dividend policies while others have annual ones. Similarly, the timing of repurchases within the calendar year varies by firm. *Distribution* is defined as either common dividends, measured both in levels and changes, or share repurchases. We scale these distributions by total assets, but results are very similar if we scale by loans, as is done for our measures of allowances and loan growth. See table A1 in the appendix for details about the variable construction.

Table 6 reports the second stage regression results using the asset-scaled measures of capital distributions. The first two columns consider levels and changes in common dividends. The last column looks at share repurchases–considering early adopters with holding companies only–hence the smaller observation count. The coefficients on the variable of interest for the dividend tests are positive, opposite the expected sign, but economically small and not statistically significant. There is not a significant change in dividend practices following the adoption of CECL. The coefficient for the repurchases test is negative but also not statistically different from zero.

Table 6: Capital Distribution Regression Results

This table shows the results of using the following specifications. The coefficient on allowance coverage (β) for the capital distribution specification is reported.

$$\begin{aligned}
\text{Distribution}_{i,t} &= \beta\,\text{AllowanceCov}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi_t\text{LoanShare}_{i,t} + \theta_i + \varepsilon_{i,t} \\
\text{AllowanceCov}_{i,t} &= \alpha\text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} \\
&\quad + \Phi_t^*\text{LoanShare}_{i,t} + \theta_i^* + \varepsilon_{i,t}^*,
\end{aligned}$$

where the control variables are defined as before and include asset quality controls, bank and loan characteristic variables, and the macroeconomic controls. Asset quality is measured by delinquency rates at 30-day, 90-day, and nonaccrual frequencies. bank characteristic variables are lagged by one period to avoid endogeneity issues and include log assets, leverage ratio, and return on assets to control for size, solvency, and profitability. $\Phi_t^*\text{LoanShare}_{i,t}$ is a vector of five variables that are equal to loan shares of five of the six loan types, and $\text{OnCECL}_{i,t}$ is a dummy variable set to one after CECL adoption by bank i.

	(1) Div/Assets	(2) ChgDiv/Assets	(3) Share Repurch/Assets (Early Adopters Only)
Allowance Coverage	0.121	0.021	-0.041
	(0.168)	(0.179)	(0.148)
Loan Type Share × Quarter Effects	Y	Y	Y
Regional Exposure × Quarter Effects	Y	Y	Y
Bank FE and Controls	Y	Y	Y
Observations	1935	1935	524

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

CECL adoption does not appear to change capital distribution behavior. However, the standard error is large enough that the coefficients would need to be large to find evidence of an effect. Thus, our evidence against an economically meaningful effect of allowances on distributions is limited.

5.4 Robustness Tests

Overall, our analysis shows that the effect of CECL adoption on allowances decreased loan growth moderately, and that this effect was stronger for more capital constrained banks. In this section, we test the robustness of these conclusions to our specific methodological approach.

First, we address concerns that two-way fixed effect estimators like ours can yield biased or counter-intuitive estimates of treatment effects when the treatment is introduced in a staggered manner and the treatment effect is possibly heterogeneous (e.g., de Chaisémartin and D'Haultfoeuille (2020) and Baker, Larcker and Wang (2022)). As a diagnostic for the magnitude of the potential issue, we estimate the implicit weighting of early and late adopters over time in the estimated average treatment effect. We find that while our estimate of average treatment effect does effectively weight some banks negatively late in the sample, the weights are small in magnitude. Thus, heterogeneity in the treatment effect would have to be fairly extreme to significantly bias our estimates.

To further address the concerns above with two-way fixed effects regressions, in table 7 column (2) we estimate our benchmark IV specification using only observations through 2022 so that late CECL adopters are effectively never-adopters within the estimation sample. As compared our bank-level IV estimate from table 4 (in column (1)), the response of loan growth to changes in allowances appears a bit stronger based on only the cohort of 2020 adopters.

Table 7: IV Regression Alternatives

This table shows the results of variations on regression equation 2, shown in column (1). Only the coefficient on allowance coverage for the loan growth (β) is reported. Column (2) includes only observations through 2022. Column (3) weights observations by dollars. Column (4) uses as instruments the CECL adoption effect interacted with an early adopter dummy and every post-adoption quarter. Column (5) reports results using synthetic IV, with a control group constructed to minimize differences in quarterly pre-CECL loan growth.

	(1) From Table 4	(2) Thru 2022	(3) Weighted	(4) IV X Qtr	(5) SIV
Allowance Coverage	-0.851*	-1.349***	-1.347***	-0.880**	-0.546
	(0.443)	(0.306)	(0.359)	(0.388)	(0.430)
Loan Share X Qtr FE	Y	Y	Y	Y	
Regional Exposure $\times$ Quarter Effects	Y	Y	Y	Y	
Bank FE and Controls	Y	Y	Y	Y	
Synthetic Control					Y
Observations (Treated Banks)	9771	8132	9771	9771	(96)

Standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The next alternative regression in column (3) is provided to test whether our conclusions hold when considering dollar-weighted observations, or the aggregate of the banks in our sample. The results are larger, meaning that larger banks tended to have larger decreases in loan growth following CECL adoption. As early adopting banks tend to be larger, the similarity of results in columns (2) and (3) is not unexpected.

The regression specification tested in column (4) revisits our choice of instrumental variable. Noting that the impact of CECL on allowances may change over time, generally reverting to the mean from the adoption impact as the firm loan portfolio and CECL models adjust, but also possibly changing in response to macroeconomic conditions. We check results when interacting the adoption effect of CECL with dummies for each post-adoption quarter in the first-stage regression as shown in equation 9. Leveraging time variation in the strength of the adoption impact instrument results in a stronger instrument overall and consequent slight reduction in standard errors, but the point estimate for the effect of allowances on loan growth is almost unchanged.

$$\begin{aligned} \text{AllowanceCov}_{it} \quad = \quad & \alpha_t^{early}\text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} + \alpha_t^{late}\text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} \\ & +\Gamma_p \,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \Phi_t^{*}\text{LoanShare}_{i,t} + \theta_i^{*} + \varepsilon_{i,t}^{*} \qquad (9) \end{aligned}$$

Lastly, we run a synthetic instrumental variable (SIV) regression, as described in Gulek and Vives-i-Bastida (2025). The SIV approach produces unbiased estimates in settings where the regressor is both endogenous and the instruments are potentially correlated with an unobserved trend. For example, given the average size difference in early and late CECL adopters in our sample, some economic shocks may affect these two groups of banks differently—even if there is no good evidence of differences in the average growth trends prior to CECL adoption. The trade off for this additional robustness is usually less statistical power.

In our application of the SIV approach, we first find synthetic control groups for each bank. We take the conventional approach of a establishing a control group for each bank that minimizes differences in quarterly pre-CECL loan growth with the bank.[33] We then ensure that the synthetic

[33]As an alternative, we first project loan growth on the adoption effect of CECL adoption on allowances. Then

controls appear reasonable and robust.[34] Next, we use the synthetic control for each bank to remove the influence of unobserved trends from the dependent, independent, and instrumental variables for each bank. Finally, an IV regression is run using this trend de-biased data spanning 2020 through 2024:Q2, following equation 10, where *db* indicates that the variable has been debiased via differencing against its synthetic control. Standard errors are constructed by bootstrapping methods where the units are banks.

$$\begin{aligned} \text{LoanGr}_{i,t}^{db} &= \beta\, \text{AllowanceCov}_{i,t}^{db} + \varepsilon_{i,t} \\ \text{AllowanceCov}_{i,t}^{db} &= \alpha(\text{AdoptionEffect}_i \times \text{OnCECL}_{i,t})^{db} + \varepsilon_{i,t}^{*} \end{aligned} \tag{10}$$

Our synthetic instrumental variables estimate is reported in column (5) of table 7. Our estimate of the effect of changes in allowances on loan growth is smaller in magnitude when using SIV; it is possible that economic conditions were less favorable to business models that led to larger CECL effect on allowances. However, the standard error is large enough that this difference is not statistically significant.

6 Conclusion

While CECL was designed to improve the timeliness of loss recognition, our results suggest that the economic effects extend beyond the accounting to real bank lending behavior. We find evidence that the general increase in loan allowances under CECL reduced lending, consistent with the literature on the effect of bank capital requirements. This lending effect was economically significant, representing about 12 percent of the average annual loan growth in our sample. Even so, the effect of CECL on lending may have been moderated by the ample regulatory capital buffers that banks had on hand during this period, and the transition rules put in place to spread the adoption effect

we construct an alternative synthetic control that minimizes differences between each bank's loan growth and other banks' loan growth projections. Gulek and Vives-i-Bastida (2025) note that this latter approach is potentially useful in situations where noise in the outcome or a short pre-event period reduces the utility of synthetic controls. However, pre-adoption loan growth is too weakly associated with adoption effect in the cross-section to provide meaningful controls.

[34] Specifically, we check (i) that the instrument is not weak (i.e., that CECL adoption effect retains predictive power over allowances), (ii) that the control groups are not "dense", i.e. do not disproportionately select a particular few banks, and (iii) that the estimator achieves a good fit in pre-adoption period backtesting.

on regulatory capital over several years.

The CECL methodology is designed to make loan loss allowances more sensitive to macroeconomic conditions. Thus, a more complete assessment of the macroeconomic impact of CECL would consider the impact of CECL on the cyclicality of loan loss allowances over the economic cycle. While CECL adopters in particular had large increases in allowances when the economic outlook changed abruptly in 2020, we will not know how well allowances will build under CECL to counter any credit risk building in the banking industry until the economy has a more standard credit cycle. Future research could explore the long-term effects of CECL on the volatility of economic growth, as well as potential policy adjustments to mitigate negative impacts on credit availability.

References

Abad, Jorge and Javier Suarez. 2018. "The Procyclicality of Expected Credit Loss Provisions." CEPR Discussion Paper No. DP13135.
URL: *https://ssrn.com/abstract=3244507*

Admati, Anat R., Peter M. DeMarzo, Martin F. Hellwig and Paul Pfleiderer. 2013. "Fallacies, Irrelevant Facts, and Myths in the Discussion of Capital Regulation: Why Bank Equity is Not Socially Expensive." Rock Center for Corporate Governance Working Paper Series NO. 161.
URL: *https://www.econstor.eu/bitstream/10419/57505/1/636811883.pdf*

Aiyar, Shekhar, Charles W. Calomiris, John Hooley, Yevgeniya Korniyenko and Tomasz Wieladek. 2014. "The international transmission of bank capital requirements: Evidence from the UK." *Journal of Financial Economics* 113(3):368–382.

Aiyar, Shekhar, Charles W. Calomiris and Tomasz Wieladek. 2014. "Does Macro-Prudential Regulation Leak? Evidence from a UK Policy Experiment." *Journal of Money, Credit and Banking* 46(1):181–214.

Baker, Andrew C., David F. Larcker and Charles C.Y. Wang. 2022. "How Much Should We Trust Staggered Difference-in-Diffrences Estimates?" *Journal of Financial Economics* 144(2):370–395.

Baker, Malcolm and Jeffrey Wurgler. 2015. "Procyclical Capital Regulation and Lending." *American Economic Review: Papers and Proceedings* 105(5):315–320.

Basel Committee on Banking Supervision. 2010. "An assessment of the Long-Term Economic Impact of Stronger Capital and Liquidity Requirements." Working Paper, December.
URL: *https://www.bis.org/publ/bcbs173.pdf*

Behn, Markus, Rainer Haselmann and Paul Wachtel. 2016. "Procyclical Capital Regulation and Lending." *The Journal of Finance* 71(2):919–956.

Bernanke, Ben S., Cara S. Lown and Benjamin M. Friedman. 1991. "The Credit Crunch." *Brookings Papers on Economic Activity* 1991(2):205–247.

Berrospide, Jose and Rochelle Edge. 2010. "The Effects of Bank Capital on Lending: What Do We Know? And, What Does It Mean?" *International Journal of Central Banking* 6(2):5–54.

Bojar, Paweł and Małgorzata Anna Olszak. 2022. "The Impact of IFRS 9 on the Link Between Lending and the Capital Ratio in Publicly Traded Banks in Poland." *Journal of Banking and Financial Economics* 17(1):60–73.

Bonaldi, Pietro, Pierre Liang and Lavender Yang. 2023. "Did CECL improve banks' loan loss provisions and earnings quality during the COVID-19 pandemic?" Working Paper.
URL: *https://ssrn.com/abstract=4360356*

Bridges, Jonathan, David Gregory, Mette Nielsen, Silvia Pezzini, Amar Radia and Marco Spaltro. 2014. "The Impact of Capital Requirements on Bank Lending." Working Paper No. 486, Bank of England.
URL: *https://www.bankofengland.co.uk/-/media/boe/files/working-paper/2014/the-impact-of-capital-requirements-on-bank-lending.pdf*

Carlson, Mark, Hui Shan and Missaka Warusawitharana. 2013. "Capital Ratios and Bank Lending: A Matched Bank Approach." *Journal of Financial Intermediation* 22:663–687.

Chae, Sarah, Robert F. Sarama, Cindy M. Vojtech and James Wang. 2021. "The Impact of the Current Expected Credit Loss Standard (CECL) on the Timing and Comparability of Reserves."

Board of Governors of the Federal Reserve System, Finance and Economics Discussion Series 2018-020.

URL: *https://doi.org/10.17016/FEDS.2018.020r1*

Chen, Jing, Yiwei Dou, Stephen G. Ryan and Youli Zou. 2025. "The Effect of the Current Expected Credit Loss Approach on Banks' Lending during Stress Periods: Evidence from the COVID-19 Recession." *The Accounting Review* 100(1):113–138.

Cohen, Benjamin H. and Jr. Gerald A. Edwards. 2017. "The New Era of Expected Credit Loss Provisioning." BIS Quarterly Review, March 2017.

URL: *https://ssrn.com/abstract=2931474*

Covas, Francisco and Gonzalo Fernandez Dionis. 2021. "Current Expected Credit Loss Methodology and Loan Growth: Evidence from the COVID-19 Event." Bank Policy Institute Note, May 2021.

URL: *https://bpi.com/wp-content/uploads/2021/05/Current-Expected-Credit-Loss-Methodology-and-Loan-Growth-Evidence-from-the-COVID-19-Event.pdf*

Covas, Francisco and William Nelson. 2018. "Current Expected Credit Loss: Lessons from 2007-2009." BPI Staff Working Paper 2018-1, July 2018.

URL: *https://bpi.com/wp-content/uploads/2018/07/CECL-Lessons-2007-2009-WP-July-12-2018.pdf*

de Chaisémartin, Clement and Xavier D'Haultfoeuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review* 110(9):2964–2996.

De Jonghe, Olivier, Hans Dewachter and Steven Ongena. 2020. "Bank capital (requirements) and credit supply: Evidence from pillar 2 decisions." *Journal of Corporate Finance* 60:101518.

Ertan, Aytekin. 2025. "Expected Losses, Unexpected Costs? Evidence from SME Credit Access under IFRS 9." *The Accounting Review* 100(4):443–473.

Fahlenbrach, Rüdiger, Minsu Ko and René M Stulz. 2024. "Bank Payout Policy, Regulation, and Politics." Working Paper Series, August 2024.

URL: *http://www.nber.org/papers/w32770*

Floyd, Eric, Nan Li and Douglas J. Skinner. 2015. "Payout policy through the financial crisis: The growth of repurchases and the resilience of dividends." *Journal of Financial Economics* 118(2):299–316.

Fraisse, Henri, Mathias Lé and David Thesmar. 2020. "The Real Effects of Bank Capital Requirements." *Management Science* 66(1):5–23.

Gambacorta, Leonardo and Paolo Emilio Mistrulli. 2004. "Does bank capital affect lending behavior?" *Journal of Financial Intermediation* 13(4):436–457.

Granja, João and Fabian Nagel. 2025. "Current Expected Credit Losses and consumer loans." *Journal of Accounting and Economics* 80(1):101781.

Gropp, Reint, Thomas Mosk, Steven Ongena and Carlo Wix. 2018. "Banks Response to Higher Capital Requirements: Evidence from a Quasi-Natural Experiment." *The Review of Financial Studies* 32(1):266–299.

Gulek, Ahmet and Jaume Vives-i-Bastida. 2025. "Synthetic IV Estimation in Panels." Working Paper.
URL: *https://ssrn.com/abstract=4716511*

Hancock, Diana and James A. Wilcox. 1993. "Has There Been a "Capital Crunch" in Banking? The Effects on Bank Lending of Real Estate Market Conditions and Bank Capital Shortfalls." *Journal of Housing Economics* 3(1):31–50.

Harris, Trevor S., Urooj Khan and Doron Nissim. 2018. "The Expected Rate of Credit Losses on Banks' Loan Portfolios." *The Accounting Review* 93(5):245–271.

Hu, Xiaoyu. 2024. "The Real Effects of Current Expected Credit Loss Provision (CECL) on Banks' Small Business Lending." Working Paper, August 22, 2024.
URL: *https://ssrn.com/abstract=4934238*

Jia, Xiaoran, Kiridaran Kanagaretnam and Haoyu Zhang. 2025. "Benefits and Consequences of CECL-Adoption During COVID-19." *Journal of Accounting, Auditing & Finance* .

Kim, Sehwa, Seil Kim, Anya Kleymenova and Rongchen Li. 2026. "Current Expected Credit Losses (CECL) Standard and Banks' Information Production." *The Accounting Review* 101(3):493–526.

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

Loudis, Bert, Sasha Pechenik, Ben Ranish, Cindy M. Vojtech and Helen Xu. 2021. "New Accounting Framework Faces Its First Test: CECL During the Pandemic." FEDS Notes, Federal Reserve Board, December 3, 2021.
URL: *https://www.federalreserve.gov/econres/notes/feds-notes/new-accounting-framework-faces-its-first-test-cecl-during-the-pandemic-20211203.html*

Mésonnier, Jean-Stéphane and Allen Monks. 2015. "Did the EBA Capital Exercise Cause a Credit Crunch in the Euro Area?" *International Journal of Central Banking* 11:75–117.

Yang, Hsiang-Chieh (Alex). 2025. "How Does Loan Loss Accounting Influence Bank Lending? Evidence from the Current Expected Credit Loss (CECL) Model." *The Accounting Review* 100(1):465–490.

A Appendix

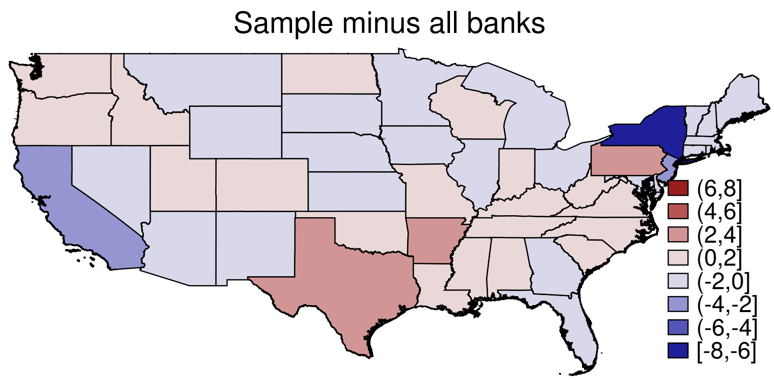
A.1 Variable Definitions

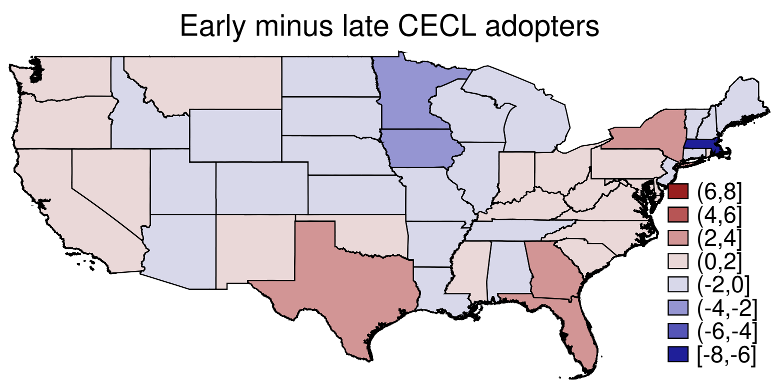
Table A1: Variable Definitions

Variable	FR Y-9C/Call Report Item	Definition
Loan balance by type	Columns A + C + E of HI/RI-C Part I	Under ILM
	Column A of HI/RI-C	Under CECL
Allowances by loan type	Columns B + D + F of HI/RI-C Part I	Under ILM
	Column B of HI/RI-C	Under CECL
Log assets	HC/RC, item 12	measured in natural logs
Tier 1 leverage	HC/RC-R Part I, item 31	
	Constructed Variables	
Loan growth	Quarterly, in percentage points as 100 * (loans$_t$/loans$_{t-1}$)-1	
Allowance coverage	Ratio of allowance for loan losses relative to loans as (allowance$_t$/loans$_t$)	
Adoption effect	Notes to the Income Statement (Other), Item 3 (JJ28), scaled by total loan balance prior to adoption	
Loan share	Ratio of loan balance by type to loan balance across all types	
Excess capital	Minimum of following ratios over any quarter 2016-2019: i) CET1 capital to 4.5% risk-based requirement, ii) Tier 1 capital to 6.0% risk-based and 4.0% leverage requirement, iii) Total capital to 8.0% risk-based requirement	
30 day delinq.	Column A of schedule HC/RC-N divided by total loan balances	
90 day delinq.	Column B of schedule HC/RC-N divided by total loan balances	
Nonaccrual	Column C of schedule HC/RC-N divided by total loan balances	
Return on assets	Four-quarter average of HI/RI, item 14	
Common dividends/ assets	Fourth-quarter year-to-date amount of HI-A, item 11 (RI-A, item 9), divided by prior year end total assets	
Share repurchases/ assets	Fourth-quarter year-to-date amount of HI-A item 8 (purchase of treasury stock) plus any negative amount reported for HI-A item 6.b (retirement of common stock), divided by prior year end total assets. As only net changes in treasury stock are reported in the Call reports, this variable is set to missing for all banks where the magnitude of net treasury stock purchases of banks not consolidated within holding companies is at some point at least 10 percent of the consolidated entity level net treasury stock purchases.	
Unemployment rate	County unemployment rate weighted by the branch locations of the bank	
Employment growth	County employment growth weighted by the branch locations of the bank	

Figure A1: Geographical Distribution of Branches

These figures plot differences in each state's share of bank branches as of the end of 2019. The top plot provides the share from the aggregate of banks in our sample minus the aggregate of all banks, while the bottom plot provides the average difference between the early and late CECL adopting banks within our sample. Branches include only main office and full service branches; banks without branches are excluded. Source: FFIEC branch data and author calculations.





A.2 Parallel Trends Tests

Figure A2: Loan Growth Effects for Early Adopters

This chart shows the coefficients $\beta_{p,t}$ from the regression equation below, where each panel represents the time series of β for a different loan portfolio p (cards = credit card loans, com = commercial and industrial loans, cre = commercial real estate loans, cnstr = construction loans, and othcons = other consumer loans), and the dependent variable Y is either loan growth (this figure) or allowance coverage (Figure A3 below). The parallel trends assumption is tested by checking whether the $\beta_{p,t}$ are jointly statistically significant from each other for those quarters t occuring prior to early CECL adoption in 2020. The Wald test p-values are indicated on the plots. Source: Call Report, FR Y-9C, and author calculations.

$$Y_{p,i,t} \quad = \quad \beta_{p,t}\,\text{EarlyAdopter}_i + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \delta_{p,t} + \theta_{p,i} + \varepsilon_{p,i,t}$$

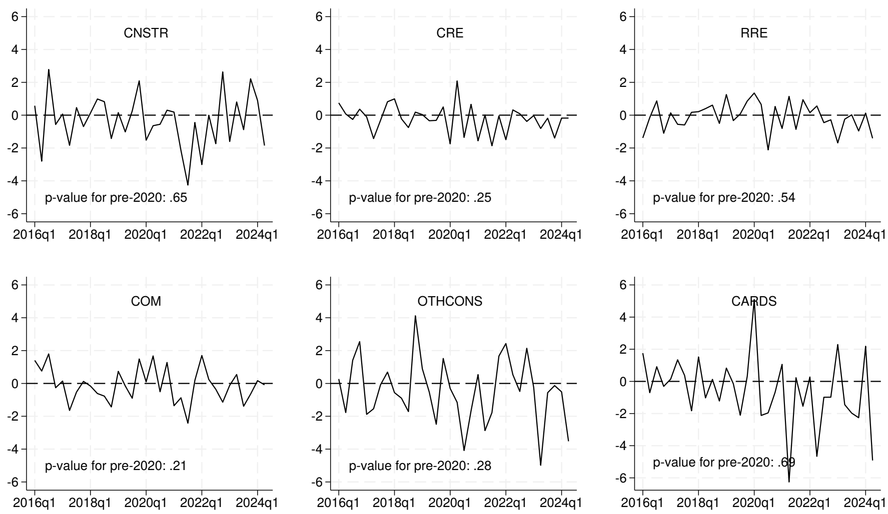
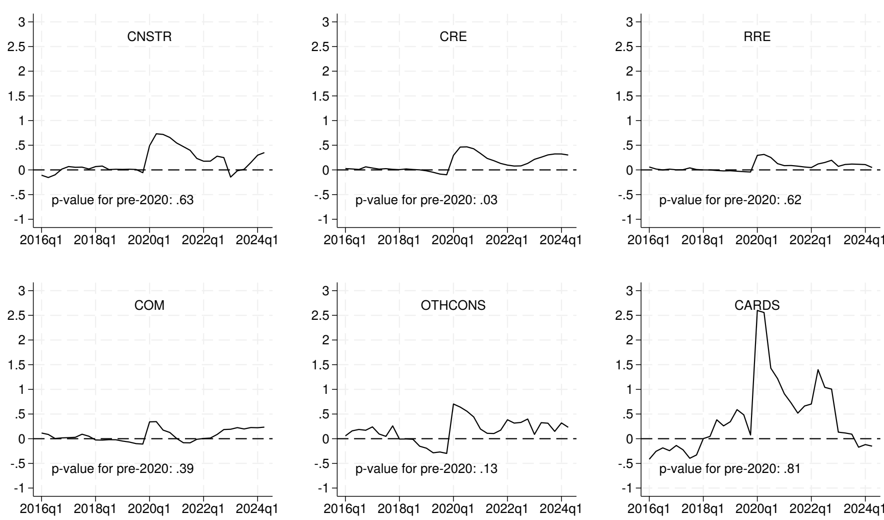


Figure A3: Allowance Effects for Early Adopters

See Figure A2 for a description.



A.3 Difference-in-Differences Test Results

Table A2: Allowance Coverage Regression Results

This table reports the allowance coverage regression results summarized by figure 3. The regression specification is:

$$Y_{p,i,t} \quad = \quad \beta_p^{early}\,\text{OnCECL}_{i,t} + \beta_p^{late}\,\text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \delta_{p,t} + \theta_{p,i} + \varepsilon_{p,i,t},$$

where Y is allowance coverage. cards = credit card loans, com = commercial and industrial loans, cre = commercial real estate loans, cnstr = construction loans, and othcons = other consumer loans.

Source: Call Report, FR Y-9C, and author calculations.

	(1) $\Delta CNSTR$	(2) ΔCRE	(3) ΔRRE	(4) ΔCOM	(5) $\Delta OTHCON$	(6) $\Delta CARDS$
OnCECL^{early}	0.331**	0.263***	0.197***	0.033	0.314*	1.081*
	(0.133)	(0.058)	(0.051)	(0.072)	(0.187)	(0.598)
OnCECL^{late}	0.274**	-0.059	0.058	-0.176**	0.008	1.111
	(0.137)	(0.055)	(0.046)	(0.078)	(0.233)	(0.712)
30-Day Delinquency Rate (pp)	0.006	0.052**	-0.011	0.010	0.221***	-0.016
	(0.018)	(0.022)	(0.014)	(0.029)	(0.072)	(0.141)
90-Day Delinquency Rate (pp)	0.242	0.055	0.018	0.238**	-0.333	0.404
	(0.238)	(0.060)	(0.028)	(0.100)	(0.225)	(0.259)
Nonaccrual Rate (pp)	0.076***	0.077***	0.081***	0.248***	0.173	0.627
	(0.025)	(0.013)	(0.019)	(0.027)	(0.158)	(0.378)
Log Total Assets	0.082	-0.037	-0.262**	-0.031	-0.134	1.822
	(0.310)	(0.118)	(0.108)	(0.141)	(0.386)	(1.604)
Lag T1 Leverage (pp)	0.073**	0.037***	0.013	0.017	0.046*	0.684***
	(0.036)	(0.013)	(0.009)	(0.012)	(0.027)	(0.211)
Return on Assets (pp)	-0.252***	-0.069**	-0.025	-0.049*	-0.195**	-1.170***
	(0.088)	(0.031)	(0.019)	(0.028)	(0.086)	(0.246)
Unemployment near Branches (pp)	-0.026	-0.013	-0.014	0.024	0.001	0.201
	(0.028)	(0.014)	(0.010)	(0.022)	(0.047)	(0.140)
Employment Growth near Branches (pp)	0.005	-0.004	-0.002	0.006	0.018	0.030
	(0.010)	(0.004)	(0.003)	(0.006)	(0.015)	(0.035)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional Exposure X Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8713	9374	9462	9372	7174	1479
R^2	0.124	0.317	0.210	0.275	0.125	0.498

Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Loan Growth Regression Estimates

This table reports the loan growth regression results summarized by figure 3. The regression specification is:

$$Y_{p,i,t} \quad = \quad \beta_p^{early}\,\text{OnCECL}_{i,t} + \beta_p^{late}\,\text{OnCECL}_{i,t} + \Gamma_p\,\text{BankControls}_{i,t-1} + \Lambda_{p,t}\,\text{Region}_{i,t-1} + \delta_{p,t} + \theta_{p,i} + \varepsilon_{p,i,t},$$

where Y is loan growth. cards = credit card loans, com = commercial and industrial loans, cre = commercial real estate loans, cnstr = construction loans, and othcons = other consumer loans.

Source: Call Report, FR Y-9C, and author calculations.

	(1) $\Delta CNSTR$	(2) ΔCRE	(3) ΔRRE	(4) ΔCOM	(5) $\Delta OTHCON$	(6) $\Delta CARDS$
OnCECL^{early}	-0.144	-0.457	0.387	-0.532	-0.838	-0.784
	(0.730)	(0.303)	(0.410)	(0.445)	(1.009)	(1.376)
OnCECL^{late}	-1.079	-0.229	0.947*	0.575	0.617	-0.260
	(0.913)	(0.359)	(0.492)	(0.464)	(0.931)	(1.111)
30-Day Delinquency Rate (pp))	-0.257	-0.609***	-0.596***	-0.797***	-2.147***	-0.877*
	(0.211)	(0.189)	(0.194)	(0.188)	(0.522)	(0.470)
90-Day Delinquency Rate (pp)	0.276	0.035	0.212	-1.598***	-3.215*	0.451
	(0.975)	(0.552)	(0.234)	(0.526)	(1.870)	(0.590)
Nonaccrual Rate (pp)	-0.196**	-0.749***	-0.555***	-0.769***	-3.937***	-0.190
	(0.088)	(0.119)	(0.159)	(0.142)	(0.869)	(0.788)
Log Total Assets	-2.159	-2.863***	-1.237	-3.888***	-1.956	-5.430**
	(1.511)	(0.746)	(0.926)	(0.896)	(2.600)	(2.696)
Lag T1 Leverage (pp)	0.217	0.175***	0.133	0.076	-0.045	-0.387*
	(0.177)	(0.060)	(0.098)	(0.108)	(0.249)	(0.214)
Return on Assets (pp)	0.396	0.199	0.456*	-0.331	-0.351	0.372
	(0.526)	(0.174)	(0.252)	(0.232)	(0.627)	(0.438)
Unemployment near Branches (pp)	-0.713***	-0.249***	-0.164	-0.260	0.603*	-0.998***
	(0.275)	(0.091)	(0.125)	(0.163)	(0.327)	(0.370)
Employment Growth near Branches (pp)	-0.222**	-0.004	-0.013	-0.030	-0.021	-0.076
	(0.098)	(0.031)	(0.046)	(0.056)	(0.083)	(0.087)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional Exposure X Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8713	9374	9462	9372	7174	1479
R^2	0.058	0.076	0.093	0.125	0.102	0.437

Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: First-Stage Coefficients

This table shows the coefficients α from the first-stage regression equations 3 (first column) and 5 (second column), as duplicated below. Source: Call Report, FR Y-9C, and author calculations.

$$\begin{aligned}\text{AllowanceCov}_{i,t} &= \alpha \text{AdoptionEffect}_i \times \text{OnCECL}_{i,t} + \Gamma_p\, \text{BankControls}_{i,t-1} + \Lambda_{p,t}\, \text{Region}_{i,t-1} + \Phi_t^* \text{LoanShare}_{i,t} + \theta_i^* + \varepsilon_{i,t}^* \\ \text{AllowanceCov}_{p,i,t} &= \alpha_p\, \text{OnCECL}_{i,t} + \Gamma_p\, \text{BankControls}_{i,t-1} + \Lambda_{p,t}\, \text{Region}_{i,t-1} + \delta_{p,t}^* + \theta_i^* + \varepsilon_{p,i,t}^*\end{aligned}$$

	Firm Level Instruments	Loan Type Level Instruments
OnCECL×		
AdoptionEffect	0.839***	
	(0.094)	
Construction		0.238**
		(0.118)
Commercial Real Estate		0.074
		(0.075)
Residential Real Estate		0.170**
		(0.068)
Commercial		-0.117
		(0.093)
Other Consumer		0.246
		(0.192)
Credit Cards		2.198***
		(0.719)
Observations	9771	45574
F Statistic	78.812	5.309

Standard errors are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.