# Current Expected Credit Losses and Consumer Loans*

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**Abstract**

We use data from TransUnion, a large U.S. credit bureau covering millions of individual consumer loans, to examine the transition to the Current Expected Credit Loss (CECL) accounting standard and its effects on banks' loan pricing and lending decisions. We find no indication that the incremental loss reserve requirements of originating a new loan under the CECL standard prompted banks to increase interest rates or to ration loan sizes to consumers. We find identical results when we exclude the months around the Covid-19 pandemic and when we restrict our attention to the group of banks with lower levels of regulatory capital. Our results are of potential interest to the ongoing policy debate between standard setters and members of the financial industry around the potential effects that CECL might have on access and price of credit.

***JEL Classification Numbers:*** *G21; G28; M41; M48*

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*TransUnion (the data provider) has the right to review the research before dissemination to ensure it accurately describes TransUnion data, does not disclose confidential information, and does not contain material it deems to be misleading or false regarding TransUnion, TransUnion's partners, affiliates or customer base, or the consumer lending industry. Zirui Song provided excellent research assistance on this project. João Granja gratefully acknowledges support of the Jane and Basil Vasiliou Research Fund at the University of Chicago Booth School of Business. Any errors or omissions are the responsibility of the authors.

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# 1 Introduction

The strong economic disruptions that followed the Global Financial Crisis of 2007–2008 sparked a contentious public debate about the causes of the crisis. Many blamed lax accounting standards that allowed financial institutions to take on large amounts of risk without setting sufficient reserves aside (e.g., Adrian and Shin [2010]; Badertscher et al. [2012]; Bischof et al. [2021]; and Laux and Leuz [2010]). In response to this debate, accounting standard setters around the world worked to overhaul the rules governing how banks determine loan loss reserves when originating loans.

In the United States, this process culminated with a shift from the incurred-loss model to the lifetime expected-loss model when determining reserves. Under the incurred-loss (IL) model, reserves are set aside only when losses are probable and can be estimated with sufficient accuracy. In practice, this approach meant that banks typically evaluated losses from homogeneous loans such as mortgages, auto loans, and consumer credit loans at the portfolio level and set reserves aside only for losses expected to occur over the next 12 to 18 months (e.g., Andrews [2018], Ryan [2019]). The expected-loss model represents a significant departure; since the adoption of the Current Expected Credit Loss (CECL) standard in the beginning of 2020, many U.S. banks and credit institutions began setting aside loan-loss reserves for the expected *lifetime* losses of a loan. CECL was intended to smooth credit cycles by ensuring that banks create robust capital buffers against potential losses during good times, which should subsequently mitigate the adverse macroeconomic impacts of negative shocks during bad times (e.g., Bernanke et al. [1999]).

While standard setters and banking regulators argue that CECL will bring positive macro-prudential effects (e.g., Schroeder [2019]), members of the financial industry have expressed deep concern about CECL's impact on banks' ability to extend credit to the economy (e.g., American Bankers Association [2019]). They argue that CECL increases banks' required credit-loss allowances, thus permanently increasing capital requirements and the cost of capital such that banks will have to pass the capital costs to consumers through higher interest rates. Furthermore, bankers claim that the heterogeneous effects of CECL across different types of loans could prompt them to adjust their product mix and pricing strategies in order to steer consumers away from lending products that have become more costly in terms of equity capital. For instance, longer-term loans became relatively more onerous in terms of credit-loss allowances because CECL requires banks to reserve for losses that are expected to occur over the *entire* life of a loan, while banks only had to cover losses expected during the first year of a loan previously. In response, the Chief Financial Officer (CFO) of Citizens Financial Group stated during an earnings call that "long-duration loans have just been assigned a capital surcharge" and that the standard would lead the bank to optimize maturities within loan categories.[1]

Despite these meaningful changes to banks' loss-reserve practices, we still know very little about the adoption of CECL and its impact on the pricing and availability of credit. Did banks' loan pricing change in response to the new rules for computing of credit-loss allowances? Did they revise lending criteria and prices across different types of loans after adopting CECL? And how did changes in the relative capital surcharges for different types of loans drive changes in banks' pricing and lending decisions?

We develop a simple model that formalizes the key economic mechanisms behind banks' claims that the adoption of CECL affects the supply and allocation of credit across loan products. The model draws inspiration from Koijen and Yogo [2015] and studies the banks' optimal loan-pricing decisions. In the model, a bank sets the prices of short- and long-term loans independently, aiming to maximize profits under a regulatory-capital constraint. When a bank originates a new loan, it sets aside a loan-loss reserve that decreases its regulatory capital accordingly. Under the IL approach,

[1] In a similar statement, the CFO of Umpqua Holdings mentioned during the company's 2019 third-quarter earnings call that CECL could result in pricing changes and lead to shorter maturities; he also did not expect movements on that front until early 2020.

banks set aside reserves for the expected losses in the first period, regardless of the duration of the loan. Under the CECL approach, banks set aside reserves for expected losses over the entire term of the loan. The first-order conditions of the bank problem suggest that banks facing a positive shadow cost for regulatory capital increase the prices of long-term loans relatively more than the prices of short-term loans following the transition to CECL. This result is not driven by any direct effect of CECL on regulatory capital; a bank substitutes away from longer-term loans whose shadow costs increase as long as the bank considers regulatory capital to be costly. Finally, our model suggests that the intensity of CECL's impact on the prices of long-term loans depends on the share of defaults expected to occur in the long run.

We use data from TransUnion, a large U.S. credit bureau covering millions of individual consumer loans, to address the questions above. These data allow us to examine the price and maturity of each individual loan, the loan's underwriter, the risk characteristics of the respective borrower, and the loan's performance over time. Importantly, a large cross-section of banks and other credit institutions report data to Transunion. Thus, we are able to observe the individual characteristics of all borrowers and can distinguish whether the originating bank did or did not adopt the CECL standard.

An important challenge in evaluating the impact of new accounting standards is determining whether the changes are driven by the adoption of the new standard or by concurrent macroeconomic events. For example, the introduction of the CECL standard by large US banks at the beginning of 2020 coincided with the COVID-19 pandemic, which caused unprecedented uncertainty in credit markets and record job losses (e.g., Chetty et al. [2020]; Granja et al. [2022]). As a result, the effects of CECL adoption are difficult to measure because the pandemic and subsequent monetary and fiscal policy responses could have had different impacts on banks depending on whether the bank adopted the CECL standard.

We exploit an institutional feature of the implementation of CECL in the U.S. to devise a strategy that allays such concerns. Unlike other accounting standard setters around the world, the Financial Accounting Standards Board (FASB) decided to implement an expected-loss method that requires the full recognition of lifetime expected losses at the inception of a loan. This U.S.-specific requirement means that bank lenders needed to increase loss reserves for long-term loans more than they did for short-term loans. We exploit this within-bank variation in the intensity of the impact of CECL adoption across loans with different maturities. Specifically, we compare the changes to relative prices and quantities of long- and short-term loans originated by banks that did and did not adopt the CECL standard. The fact that the intensity of CECL's effects varies among different loan maturities within the same bank and period enables us to use a triple-differences specification that is less likely to be confounded by economic forces that influence both a bank's adoption of CECL and the overall interest rates offered by CECL-adopting banks.

We focus on the markets for auto and personal unsecured loans in the U.S. These markets are sizable, with total values of approximately $1.3 trillion and $180 billion, respectively, and they account for approximately 10% of the loan portfolios of all U.S. commercial banks. Thus, small changes in prices and lending decisions will meaningfully affect consumer welfare and bank profits. These markets give us rich variation in loan duration, as banks offer auto and personal-unsecured loans of very different maturities. Auto loans typically have terms ranging from 36 to 84 months and personal-unsecured loan maturities range from 6 to 72 months. In contrast to the markets for mortgages and student loans, which are heavily distorted by government intervention, (e.g., Hurst et al. [2016], Looney and Yannelis [2022]), prices and quantities in the auto and personal-unsecured loan markets are largely determined by competitive forces. As a result, we can use the transition to the CECL approach in these markets as a means of understanding the effects of CECL in a setting in which prices and quantities are set in a relatively competitive market.

We begin our empirical analysis by describing basic facts about the prices, quantities, and historical loan performance of auto and personal unsecured loans across different maturities. We show that the events of the pandemic disrupted these markets during 2020. The total amount of all loans originated by banks declined by about 50% in March 2020, recovering to pre-pandemic levels over the following months. Interest rates for auto and personal-unsecured loans also decreased, potentially due to the Federal Reserve's loosening of monetary policy in response to the crisis. Our analysis also reveals that CECL-adopting and non-adopting banks responded differently to the pandemic. These findings highlight that potential confounders like differences in exposure to demand and monetary-policy shocks must be considered when evaluating the impact of CECL on loan markets.

Our initial difference-in-differences approach compares the interest rates set by CECL-adopting and non-adopting banks before and after the policy change. We include a battery of fixed effects to control for confounding factors like time-varying changes in loan pricing for borrowers with different credit scores, overall shocks to the prices of loans across different maturities, invariant differences in the pricing of loans across different maturities, and invariant spatial differences in loan pricing related to differences in local competitive conditions (e.g., Argyle et al. [2020]). Our point estimates suggest that the adoption of CECL had no effect on the inerest rates of CECL-adopting banks relative to those of non-adopting banks, with confidence intervals that are precise enough to reject a modest increase of more than six percent in the loan rates of CECL-adopting banks. These results are nevertheless vulnerable to the criticism that we might be capturing the impact of unobservable confounding factors that affect the pricing policies of CECL-adopting banks differently than they do with other banks.

To address this concern, we implement a triple-differences specification that exploits the aforementioned variation in the intensity of the impact of CECL across different loan maturities within the same bank and type of loan. The results from this research design also show that the effects of CECL adoption on loan pricing were modest. Our results suggest that a one-standard deviation increase in the share of lifetime defaults occurring beyond the first year of the loan's term is associated with an increase of 1.4% in the interest rates of long-term loans relative to short-term loans. Moreover, we also reject that CECL had large effects on interest rates with this alternative specification.

A possible explanation for the small estimated impact of the adoption of CECL on consumer interest rates is that most banks were well-capitalized and therefore faced a low shadow cost of regulatory capital during the transition to the new standard. Thus, the relative increase in the amount of loss reserves associated with long-term loans did not significantly affect optimal pricing and lending decisions because most banks' regulatory capital constraints were not binding, such that they did not need to adjust prices and quantities to conserve capital. We examine if the impact of the transition to the CECL standard is more pronounced for banks with lower levels of Tier-1 capital, which are more likely to be capital constrained. The results are unchanged; banks with below-median Tier-1 capital ratios do not see greater effects of CECL on interest rates. This result is consistent with studies (e.g., Blank et al. [2020]; Li et al. [2020]) that argue that even banks with below-median Tier 1 capital ratios were reasonably well capitalized around the adoption of the CECL standard. Moroever, actions by regulators allowing banks to phase in adoption of CECL through 2025 might have allowed CECL-adopting banks to temporarily avoid the impact of CECL on regulatory capital which, in turn, allowed these banks to keep their loan-pricing policies unchanged.

Finally, we evaluate whether our inability to find economically and statistically significant impacts of CECL adoption on consumer loan rates reflects banks' rationing the size of new loans rather than adjusting loan prices. Our findings again fail to suggest that CECL-adopting banks are rationing the average size of long-term loans relative to short-term loans. Overall, our findings seem to be most consistent with the idea that banks were generally very well-capitalized at the onset of the

COVID-19 pandemic, insulating them from the feared effects of adopting CECL.

This paper contributes to an established literature that examines how loan-loss provisioning practices shape credit cycles and lending practices. Beatty and Liao [2011] show that banks with timelier provisions reduce lending less during economic downturns and Bushman and Williams [2012] use a cross-country approach to show that greater reliance on forward-looking information when setting provisions for loan losses can mitigate bank risk-taking but only if the forward-looking information is not used to artificially smooth earnings. Jiménez et al. [2017] have found that lending is less cyclical when banks are forced to adopt dynamic provisioning practices. Recently, Chen et al. [2022] find that banks that adopted CECL reduced their overall lending more than others during the COVID-19 downturn and Bischof et al. [2022] finds that lenders cut lending to borrowers most at risk of requiring additional provisions.[2]

Our main goal is not to assess whether CECL affected the cyclicality of lending standards, but rather we want to evaluate the claim that the lifetime expected cost model will permanently raise interest rates for consumer loans. Our contribution lies in exploiting a highly granular data set to devise an empirical strategy that leverages specific institutional features of the adoption of CECL to estimate its impact on the cost of consumer credit. Our finding that CECL had no significant impact on the price of credit is novel and is dissonant with the findings of papers (e.g., Ertan [2021]; Lin et al. [2021]) that have used different designs to evaluate how the adoption of expected-credit loss models affects the price of credit. In this sense, the present paper makes an important contribution to the ongoing policy debate between standard setters and members of the financial industry around the CECL's effects on credit access and pricing.[3]

[2] An emerging literature examines the impact of the adoption of CECL and IFRS 9 on lending and lending cyclicality. Chae et al. [2018], Abad and Suarez [2018], and Mahieux et al. [2020] have simulated theoretical models to better understand how the adoption of new standards might affect bank lending.

[3] The paper also relates more broadly to the literature that examines the effects of the IFRS 9 and CECL accounting standards on bank operations. López-Espinosa et al. [2021] and Kim et al. [2022] argue that banks who adopt forward-looking provisioning practices make investments in internal control systems, which in turn make

The paper also contributes to a strand of the literature in banking and finance that examines the impact of tighter regulatory capital requirements on the cost of capital borne by banks, consumer access to credit, and overall economic outcomes. Gropp et al. [2019] find that higher capital requirements have led European banks to rebalance their portfolios away from high-risk-weighted assets. Kisin and Manela [2016] exploit information about banks' use of a costly regulatory loophole to estimate the cost banks pay for equity capital and estimate a modest effect for capital requirements on banks' cost of capital. A series of related papers examine the impact of model-based regulations to determine the risk weights associated with each bank loan. Behn et al. [2016], Behn et al. [2022], and Benetton [2021] find that these model-based regulations affect the risk weights across loans and banks and that such differences have implications for the supply of credit. Our paper uses the "lifetime losses" feature of the implementation of the CECL standard in the U.S. to elicit variation in capital surcharges across different maturities of loans originated by the same bank. We use this variation to estimate how strongly capital requirements affect bank lending. Unlike other papers, we find that changes in capital surcharges have no significant effect on consumers' cost of credit.

# 2 Model

## 2.1 Setup

This section presents a simple framework in which a bank sets the interest rates of loans with different maturities subject to a capital constraint. The model has three periods. At time $t = 0$, the bank makes short-term loans, $A^s$, that mature in period 1 and long-term loans, $A^l$, that mature in period 2. The short-term loan defaults at the end of period 1 with probability $\delta_s$. The probability

their provisions more informative of future losses. Gee et al. [2022] find that day-1 provisions are informative when predicting credit losses. Harris et al. [2018] and Lu and Nikolaev [2021] develop structural methods to understand which sources information might be most useful in predicting future losses.

that a long-term loan defaults at the end of period 1 is $\delta_l^1$ and the probability that it defaults at the end of period 2 is $\delta_l^2$. The lifetime probability of default of a long-term loan is therefore given by: $PD_l = \delta_l^1 + (1-\delta_l^1)\delta_l^2$. We assume that all lending opportunities are positive net present value and that lenders are not able to recover any losses in case of default. Taken together, these assumptions imply that the rates of return on short-term and long-term loans exceed their respective lifetime probability of default $r_1^s > \delta_s$ and $r^l > PD_l$. Banks' expected profit at the end of period 1 are:

$$E[\Pi^1] = \underbrace{r_1^s A_1^s}_{\text{short loan income}} + \underbrace{r^l A^l}_{\text{long loan income}} - \underbrace{\delta_s A_1^s}_{\text{short loan loss}} - \underbrace{\delta_l^1 A^l}_{\text{long loan loss}} - r_D D - C \tag{1}$$

at the end of period 1, the bank reinvests outstanding funds in short-term loans and earns expected profits:

$$E[\Pi^2] = \underbrace{r_2^s A_2^s}_{\text{short loan income}} + \underbrace{r^l(1-\delta_l^1)A^l}_{\text{long loan income}} - \underbrace{\delta_s A_1^2}_{\text{short losses}} - \underbrace{\delta_l^2(1-\delta_1^l)A^l}_{\text{long losses}} - r_D D - C \tag{2}$$

The banks' investments in $A_1^s$ and $A^l$ are financed by a mix of deposits and total equity such that:

$$A_1^s + A^l = D_0 + E_0 \tag{3}$$

The bank is subject to a leverage constraint at time $t = 0$ which is defined by:

$$\frac{E_0 - LLP}{A^l + A^s - LLP} \geq k \tag{4}$$

We model the bank's decision to make homogeneous loans whose expected losses over a short horizon can be estimated at the portfolio level. For this type of loans, the key difference between the incurred loss and expected loss models is the horizon over which banks have to provision. Under the IL model, banks provision at time $t = 0$ for the expected losses in period 1 :

$$LLP_{ILM} = \delta_s A_1^s + \delta_l^1 A^l. \tag{5}$$

Under the CECL model, banks provision at origination for the expected losses over the entire loan horizon. Banks, therefore, also provision for the expected second-period losses of the long-term loan at time $t = 0$:

$$LLP_{CECL} = \delta_s A_1^s + (\delta_l^1 + \delta_l^2(1 - \delta_1^l))A^l \tag{6}$$

## 2.2 Demand

We assume that banks face a downward-sloping demand for their lending products. This assumption reflects the commonly-held idea that banks will have some degree of market power at the local level given frictions that impede local consumers from borrowing from faraway lenders. We could alternatively microfound the banks' demand from a model of consumer choice with search frictions as in Argyle et al. [2020]. For parsimony, we assume that a bank's demand function for each type of loan is exogenously given by:

$$A^i = q^i(r^i) \tag{7}$$

## 2.3 Optimal Loan Pricing

A bank chooses rates for each type of loans to maximize the expected sum of profits over the two periods subject to balance sheet and leverage constraints. Under the incurred loss model, the leverage constraint is only affected by provisions that cover the expected period 1 loan losses on both types of loans. The banks' maximization problem is:

$$
\begin{aligned}
max_{r_1^s, r_2^s, r^l} \quad r^s A_1^s + r^l A^l - \delta_s A_1^s - \delta_l^1 A^l - r_D D - C \\
+ r^s(1-\delta)A_1^s + r^l(1-\delta_l^1)A^l - \delta_s(1-\delta)A_1^s - \delta_l^2(1-\delta_l^1)A^l - r_D D - C
\end{aligned}
\tag{8}
$$

s.t.

$$
E_0 - \delta_s A_1^s - \delta_l^1 A^l - ((1-\delta_l^1)A^l + (1-\delta_s^1)A^s)k \geq 0 \tag{9}
$$

let $\lambda$ be the Lagrange multiplier on the leverage constraint (4). The Lagrangian for the bank's maximization problem under the incurred loss model is:

$$
\mathcal{L} = E[\Pi^1] + E[\Pi^2] + \lambda(E_0 - \delta_s A_1^s - \delta_l^1 A^l - ((1-\delta_l^1)A^l + (1-\delta_s^1)A^s)k) \tag{10}
$$

and the first order condition for the rate of the long-term loan is

$$
\frac{\partial L}{\partial r^l} = \frac{\partial \Pi^1}{\partial r^l} + \frac{\partial \Pi^2}{\partial r^l} + \lambda\left(-\delta_l^1 \frac{\partial A_1^l}{\partial r^l} - k(1-\delta_l^1)\frac{\partial A^l}{\partial r^l}\right) = 0 \tag{11}
$$

rearranging the FOC, we can express the rate on the long term loan as:

$$
r^l = \left(1 - \frac{1}{|\epsilon^l|}\right)^{-1} \frac{PD}{2-\delta_l^1}\left(1 + \lambda \frac{\delta_l^1 + k(1-\delta_l^1)}{PD}\right) \tag{12}
$$

That is, the long-term loan rate is determined by a markup on the marginal cost of the loan, which is the annualized probability of default of the loan over the two periods plus a factor that depends on the shadow cost of regulatory capital, $\lambda$, and on the ratio between the probability of default of the long-term loan in the first period and the expected lifetime probability of default of the loan.[4]

Under CECL, banks must provision for the expected lifetime losses of the loan at its loan origination, which affects the regulatory capital constraint at time $t = 0$. However, apart from these

[4]The factor $2 - \delta_l^1$ is credit market specific. In credit markets the posted price does not correspond to the paid price when people default. The factor corresponds to the expected number of interest collections.

changes to the regulatory capital constraint, the bank maximization problem is not affected and we obtain the following first-order condition:

$$r^l = \left(1 - \frac{1}{|\epsilon^l|}\right)^{-1} \frac{PD}{2 - \delta_l^1} \left(1 + \lambda \frac{PD + k(1 - PD)}{PD}\right). \tag{13}$$

The pricing of the long-term loan between the CECL and IL standard is different because the CECL bank fully recognizes lifetime losses at $t = 0$. This full recognition of lifetime losses magnifies the effects of the shadow cost of capital on loan pricing.

The pricing rule for the rates of short-term loans does not differ across the incurred loss and expected loss models because the full lifetime losses of short-term loans are entirely estimable and predictable at $t = 0$. The first order condition with respect to the rate of short-term loans is:

$$r_s = \left(1 - \frac{1}{|\epsilon^s|}\right)^{-1} \frac{PD_s}{2 - \delta_1^s} \left(1 + \lambda \ \frac{\delta_s^1 + k(1 - \delta_s^1)}{PD_s}\right) \tag{14}$$

Our empirical predictions follow straight from the above first-order conditions of the banks maximization problem. Due to the increased capital charge for long-term loans, the long-short rate differential is larger under expected loss than under the incurred loss model. To see this, note that assuming similar demand elasticities, default probabilities, and approximately unchanged shadow cost of capital under IL and CECL, the rate differential simplifies to:

$$ln(r^l_{CECL}) - ln(r_s) - (ln(r^l_{ILM}) - ln(r_s)) \approx \lambda(1 - k) \left(1 - \frac{\delta_l^1}{PD}\right) \tag{15}$$

Equation (15) shows that the difference between the interest rate of long- and short-term loans under the CECL and IL model increases in the bank's shadow cost of capital and in the share of defaults of the long-term loan that occurs in period $t = 2$. The interest rates across different types of loans within the same bank may change even if the shadow cost of regulatory capital, $\lambda$, does not. The reason is that there is a substitution effect from long-term to short-term loans because the former become relatively more expensive in terms of regulatory capital. Banks re-optimize their pricing strategies and product allocation mix if they believe that that their regulatory equity capital is privately costly, $\lambda > 0$. This result formalizes some claims by representatives of the financial industry that CECL implies an increase in the cost of credit for certain types of loans.

### 2.4 Identifying Assumptions and Empirical Strategy

In this section, we describe how our framework shapes our empirical strategy and how we use it to better understand what are the necessary conditions under which our difference-in-differences and triple-differences specifications identify our parameter of interest.

In a standard difference-in-differences design, the Average Treatment Effect on the Treated (ATT) can be identified under a common trends assumption. This assumption implies that the interest rates for CECL-adopting banks would have evolved similarly to the interest rates of non-adopting banks had CECL banks not adopted CECL:

$$E[ln(r^l_{j,Post}(0)) - ln(r^l_{j,Pre}(0))|CECL_j = 1] = E[ln(r^l_{j,Post}) - ln(r^l_{j,Pre})|CECL_j = 0] \tag{16}$$

In the context of the framework that we discussed above, the common trends assumption implies three conditions: (i) it requires that the markup, $-ln\left(1 - \frac{1}{|\epsilon|}\right)$, of CECL adopters and non-adopters would have evolved similarly had CECL-adopters not adopted CECL,

$$E\left[-ln\left(1-\frac{1}{|\epsilon^l_{j,Post}(0)|}\right)+ln\left(1-\frac{1}{|\epsilon^l_{j,Pre}|}\right)\middle|CECL_j=1\right]$$
$$=E\left[-ln\left(1-\frac{1}{|\epsilon^l_{j,Post}|}\right)+ln\left(1-\frac{1}{|\epsilon^l_{j,Pre}|}\right)\middle|CECL_j=0\right], \tag{17}$$

(ii) it requires that the annual probabilities of default, $ln\left(\frac{PD}{2-\delta^1}\right)$, would have evolved similarly for both groups of banks,

$$E\left[ln\left(\frac{PD_{j,Post}(0)}{2-\delta^1_{j,Post,l}(0)}\right)-ln\left(\frac{PD_{j,Pre}}{2-\delta^1_{j,Pre,l}}\right)\middle|CECL_j=1\right]$$
$$=E\left[ln\left(\frac{PD_{j,Post}}{2-\delta^1_{j,Post,l}}\right)-ln\left(\frac{PD_{j,Pre}}{2-\delta^1_{j,Pre,l}}\right)\middle|CECL_j=0\right], \tag{18}$$

(iii) it also requires that the shadow cost of capital would have trended similarly across both groups if not for the adoption of CECL

$$E\left[\lambda_{j,Post}(0)\frac{\delta^1_{l,j,Post}(0)+k(1-\delta^1_{l,j,Post}(0))}{PD_{j,Post}(0)}-\lambda_{j,Pre}\frac{\delta^1_{l,j,Pre}+k(1-\delta^1_{l,j,Pre})}{PD_{j,Pre}}\middle|CECL_j=1\right]$$
$$=E\left[\lambda_{j,Post}\frac{\delta^1_{l,j,Post}+k(1-\delta^1_{l,j,Post})}{PD_{j,Post}}-\lambda_{j,Pre}\frac{\delta^1_{l,j,Pre}+k(1-\delta^1_{l,j,Pre})}{PD_{j,Pre}}\middle|CECL_j=0\right]. \tag{19}$$

To illustrate why a difference-in-differences or a triple-differences specification could help us identify the average treatment effect on the treated parameter, let us suppose that the markup, $-ln\left(1-\frac{1}{|\epsilon|}\right)$, can be modeled in terms of an additive structure for potential outcomes that depends on loan maturity and bank characteristics that may or may not vary over time:

$$-ln\left(1-\frac{1}{|\epsilon^i_{j,t}|}\right)=\theta_j+\gamma_{j,t}+\omega_{i,t}+\mu_{i,j,t} \tag{20}$$

where $\theta_j$ is a set of bank characteristics, $\gamma_{j,t}$ is a vector of time-varying bank characteristics that affect the markup, $\omega_{i,t}$ is a set of maturity-specific characteristics that change over time, and finally $\mu_{i,j,t}$ represents time-varying characteristics of the loans that each bank originate within a specific maturity. When we consider a difference-in-differences approach, in which we compare banks that adopted CECL with banks that did not adopt CECL both before and after the adoption of the standard, we can use the additive structure of equation (20) to express the common trends assumption in equation (17) as:

$$\Delta\gamma_{CECL=1} - \Delta\gamma_{CECL=0} + \Delta\mu_{l,CECL=1} - \Delta\mu_{l,CECL=0} = 0 \tag{21}$$

The above equation indicates that for the common trends assumption to hold, selection onto the CECL standard must be orthogonal to changes in characteristics that affect the demand elasticities and markups of banks, $\Delta\gamma$, and also orthogonal to changes in the bank-specific characteristics that specifically affect the markup of long-term maturity loans, $\Delta\mu$. We could make very similar arguments for the common trends assumptions associated with the other components of the first order condition of the bank's maximization problem in equations (18) and (19).

The condition of equation (21) is restrictive when we consider the sizable macroeconomic shocks that affected the economy following the Covid-19 crisis and the fact that the largest banks in the economy adopted the CECL standard. For instance, larger banks that adopted CECL possibly serve systematically different locations and clienteles and, in the absence of CECL, the markups and probabilities of default of CECL-adopting banks might have been affected differently by the events of the pandemic.

We extend this framework to a triple-differences specification to relax these assumptions. In this triple-differences specification, we compare the difference between the changes in outcomes of long-term and short-term loans before and after the adoption of CECL for banks that adopt and do not adopt the new standard. Using this triple-differences approach, we can express the common trends assumption associated with the markup as:

$$
\begin{aligned}
&E\left[-ln\left(1-\frac{1}{|\epsilon^{l}_{j,Post}(0)|}\right)+ln\left(1-\frac{1}{|\epsilon^{l}_{j,Pre}|}\right)+ln\left(1-\frac{1}{|\epsilon^{s}_{j,Post}|}\right)-ln\left(1-\frac{1}{|\epsilon^{s}_{j,Pre}|}\right)\middle|CECL_j=1\right]\\
=&E\left[-ln\left(1-\frac{1}{|\epsilon^{l}_{j,Post}|}\right)+ln\left(1-\frac{1}{|\epsilon^{l}_{j,Pre}|}\right)+ln\left(1-\frac{1}{|\epsilon^{s}_{j,Post}|}\right)-ln\left(1-\frac{1}{|\epsilon^{s}_{j,Pre}|}\right)\middle|CECL_j=0\right]\\
\iff &[\Delta\mu_{l,CECL=1}-\Delta\mu_{s,CECL=1}]=[\Delta\mu_{l,CECL=0}-\Delta\mu_{s,CECL=0}].
\end{aligned}
\tag{22}
$$

The condition of equation (22) is now less restrictive than the common trends assumption underlying the simple difference-in-differences specification. It indicates that the demand elasticities and markups of CECL adopters can trend differently from those of non-adopters as long as the difference between the trends of the markups, probabilities of default, and shadow cost of capital of long- and short-term loans are similar across CECL-adopters and non-adopters. Put differently, the common trends assumptions underlying the triple-differences specification requires that bank-specific shocks that affect the markups of a specific maturity but not others are similar across CECL adopters and non-adopters.

If we assume that the common trends assumption is satisfied, it follows from equation (15) that the average treatment on the treated effect can be expressed as:

$$
\begin{aligned}
ATT \equiv E&\left[ln(r_{j,Post}(1))-ln(r_{j,Post}(0))\middle|CECL_j=1,long=1\right]\\
=E&\left[\lambda_{Post}(1-k)\left(1-\frac{\delta^{1}_{Post,l}}{PD_{Post}}\right)\middle|CECL_j=1,long=1\right].
\end{aligned}
\tag{23}
$$

The above equation indicates that a standard difference-in-differences specification estimates a parameter of interest that can be interpreted as the expected value across all loans of the shadow cost of capital of the bank originating the loan multiplied by the share of defaults on the loan occurring in the long-run. Because the TransUnion dataset allows us to obtain information on the historical default rate profile over time for each type and loan maturity, we can lever that information to compute $\left(1 - \frac{\delta^1_{Post,l}}{PD_{Post}}\right)$ for each loan type and maturity. That would allow us to estimate a triple-differences specification that exploits differences in the impact of CECL across types of loans within a bank and time. The average treatment on the treated effect of a triple-differences specification estimates the shadow cost of regulatory capital parameter for the banks that adopted CECL.

If the regulatory capital constraints of CECL banks were very tight around the adoption of CECL, we might expect significant substitution from maturities with high ratios of lifetime losses to one-year losses. If, on the other hand, equity capital is relatively cheap and CECL banks had abundant levels of regulatory capital, it is less likely that their loan pricing is affected by relative changes in the shadow prices of each type of loan and maturity in the regulatory capital constraint. Our empirical model will therefore examine if the evolution of loan interest rates across CECL and non-CECL banks is consistent with claims that equity is very costly for banks and that CECL will force them to shift from long- to short- loan maturities.

# 3 Data and Descriptive Statistics

The Booth TransUnion Consumer Credit Panel is a 10% sample of all TransUnion credit records. A small fraction of individuals leave the panel each month (e.g., death) and to maintain the representativeness of the sample, a random 10% sample of individuals is added to the panel. Keys et al. [2023] provides more details about the Booth Transunion Consumer Credit Panel. The data contains basic information about consumer loans including the type of loan, original balance, current balance, scheduled payments, maturity of the loan, and delinquency status. Moreover, the data set also allows us to observe borrower information such as their age, location, or credit score. We do not directly observe the interest rates of a loan on the TransUnion data set. We employ the annuity formula to impute interest rates for loans with constant scheduled payments. We plug scheduled payments (A), loan maturity (t), and initial loan amount (P) into the annuity formula $A = \frac{P \times i}{1-(1+i)^t}$ and solve for the implied interest rate, $i$, using a root-solving algorithm. Importantly, we rely on scheduled, not realized payments to compute interest rates. Yannelis and Zhang [2021] and Jansen et al. [2022] employ a similar methodology to impute interest rates for auto loans. We refer to these papers for additional details and robustness tests concerning the validity of this procedure.

To protect individual privacy and lender proprietary information, the data is anonymized. We obtained information on the adoption of CECL and capital ratios from the publicly-available regulatory call reports and we worked with TransUnion to create a mechanism to add CECL adoption flags to the credit panel while preserving lender anonymity in the credit panel. The process involved the following steps. First, TransUnion provided us with a list of names of financial institutions in the US. Second, we matched key flags to the list of financial institutions provided by TransUnion using a combination of hand and fuzzy string matching. Subsequently, TransUnion added anonymized lender keys to the file and removed financial institution names. Lastly, we merged the anonymized file containing CECL adoption dummies and Tier 1 capitalization deciles to the Booth Consumer Credit Panel provided by TransUnion.

Next, we document descriptive statistics concerning certain outcomes and characteristics of the market for auto and personal unsecured loans. We also present time-series that describe the evolution of loan amounts and interest rates over the sample period and summary statistics that describe the probabilities of default across loans of different maturities. We begin our descriptive analysis by presenting aggregate information about these loan markets from January 2018 to March 2022. Panel A of Table 1 provides summary statistics for our sample of auto loans. Auto loans have an average interest rate of 5% and loan size of 26,421 USD. The average credit score is 736, indicating that the average auto loan goes to borrowers with good credit scores. The share of defaults that occur after the first year of a loan is approximately 61%, which suggests that the average loan experiences increases in loss reserves once full recognition of lifetime losses at inception is required under CECL. The average maturity is 5.63 years and approximately 79% of auto loans is made by CECL adopters.

Panel B summarizes the sample of unsecured installment loans. Average interest rates are higher than in the auto sample at 12%, and loan sizes are smaller at 12,185 USD. The average borrower of a personal unsecured loan has a credit score of 712, which is lower than that of the average borrower of an auto loan. Half of all defaulted loans in this category default after the first year since the loan inception. Approximately 71% of the personal unsecured bank loans are made by CECL-adopting banks.

Figure (1a) plots the evolution of the average interest rates of bank-issued auto loans over the sample period across different maturities. The figures show that longer-term loans tend to have higher interest rates than shorter-term loans. The average interest rates across maturities varied between 4.5% and 6.5% until the beginning of 2020. Following the pandemic, the average interest rates declined across all maturities and stabilized at a lower level during 2021.

In Figure (1b), we present information concerning the evolution of the total volume of loans across different maturities. This plot shows that the aggregate market size of longer-term auto loans is greater than that of shorter-term loans. The only exception is the 7-year auto-loan market, whose market size is smaller than that of the six-year auto-loan market. The loan volumes across all maturities see a significant decline of approximately 30% during March 2020 but quickly recover to pre-pandemic levels in the following months.

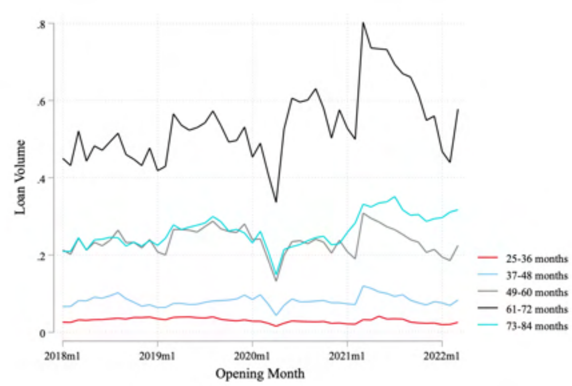
Table 1: Summary statistics

| | Count | Mean | Sd | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| *Panel A: Auto* | | | | | | |
| Interest Rate | 2,123,380 | 0.05 | 0.02 | 0.03 | 0.05 | 0.06 |
| Loan Amount | 2,123,380 | 26,421 | 11,745 | 17,495 | 25,000 | 34,184 |
| Credit Score | 2,123,380 | 736 | 66 | 690 | 746 | 792 |
| $1 - \frac{One\text{−}year}{Lifecycle}$ | 2,123,380 | 0.61 | 0.06 | 0.61 | 0.64 | 0.64 |
| Maturity | 2,123,380 | 5.63 | 1.04 | 5.00 | 6.00 | 6.00 |
| Adopter | 2,123,380 | 0.79 | 0.40 | 1.00 | 1.00 | 1.00 |
| *Panel B: Unsecured* | | | | | | |
| Interest Rate | 617,981 | 0.12 | 0.04 | 0.09 | 0.11 | 0.14 |
| Loan Amount | 617,981 | 12,185 | 9,003 | 5,000 | 10,000 | 18,000 |
| Credit Score | 617,981 | 712 | 66 | 668 | 719 | 760 |
| $1 - \frac{One\text{−}year}{Lifecycle}$ | 617,981 | 0.48 | 0.17 | 0.49 | 0.52 | 0.60 |
| Maturity | 617,981 | 3.78 | 1.47 | 3.00 | 4.00 | 5.00 |
| Adopter | 617,981 | 0.71 | 0.45 | 0.00 | 1.00 | 1.00 |

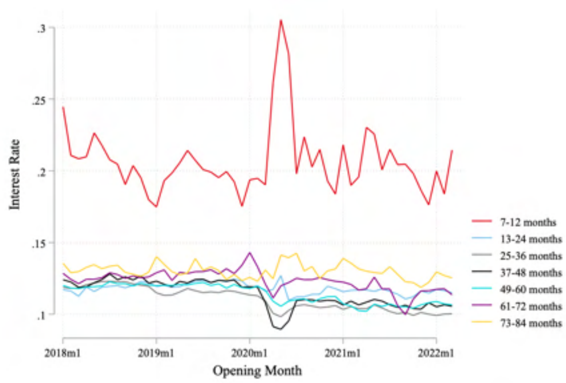
This table displays basic summary statistics for the main variables. *Interest rate* is the implied interest rate of an individual loan. *Loan Amount* is the principal amount of each loan. *Credit Score* is the individual credit score of the borrower at the origination of the loan. $\left(1 - \frac{One\text{-}year}{Lifecycle}\right)$ is one minus the ratio between the average probability of default in the first year and the lifetime probability of default for each type and maturity of loan. This ratio is computed using pre-CECL data. *Maturity* is the loan maturity (in years). *Adopter* is a dummy variable that takes the value of one for CECL adopters. Source: TransUnion.

Figure 1: Aggregate Loan Rates and Volumes by Maturity Issued by Banks

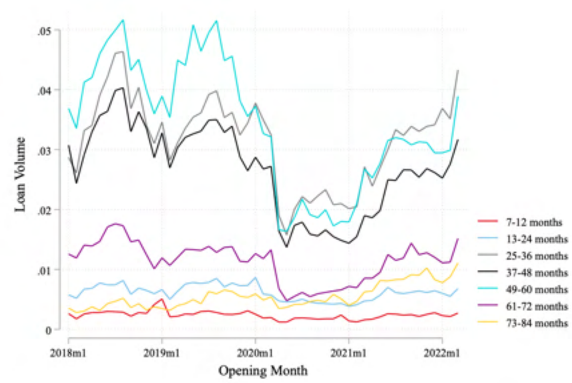

(a) Auto Interest Rates




(b) Auto Loan Volumes




(c) Unsecured Interest Rates




(d) Unsecured Loan Volumes

This figure shows the monthly evolution of interest rates and aggregate loan amounts for each type of loan and maturity between January 2018 and March 2022. Loan volumes are in billion USD.

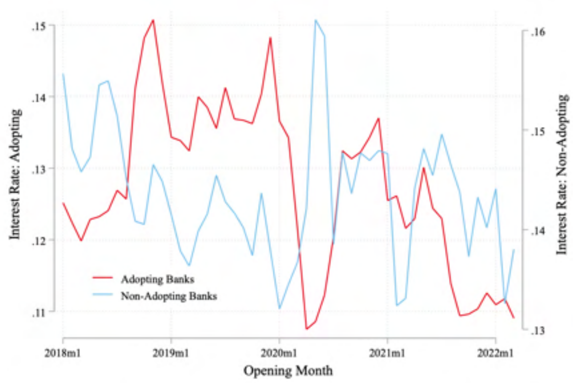
Figure (1c) plots the average interest rates for personal unsecured installment loans across all maturities. The average interest rates in this market vary between 10% and 15% across most maturities with the exception of 7–12 months loans whose average interest rates exceed 20%. The average interest rates across these loans initially move closely together but exhibit greater dispersion across maturities after the pandemic. Figure (1d) shows the corresponding loan volumes. The aggregate amount of personal unsecured loans originated with maturities between three and five years substantially exceeds the aggregate amount of personal unsecured loans originated with other maturities. Aggregate lending in the personal unsecured credit market also declines by approximately 30% during the pandemic but recovers more gradually than aggregate lending in the market for auto loans.

Next, we take a simple cut of the raw data and examine the evolution of the average interest rates and aggregate lending of commercial banks that did and did not adopt the CECL standard. We restrict the sample of CECL-adopting banks to banks that adopted the standard in the first quarter of 2020, which is a group that comprises the vast majority of banks that adopted CECL. Focusing our attention on those banks allows us to keep the events in calendar time and to have a sufficiently long post period which is desirable given the onset of the pandemic right after the adoption of the CECL standard. We present these results in Figures (2a) and (2b) for auto loans and Figures (2c) and (2d) for personal unsecured installment loans. Figure (2a) shows that the average interest rates of banks that adopted the CECL standard is lower than the average interest rate of other commercial banks throughout the entire sample period. The figure also shows that the decline in the average interest rates of auto loans originated by CECL-adopters after the pandemic was faster than that of non-CECL adopters over the same period. Because the largest U.S. banks have adopted CECL during the first quarter of 2020, Figure (2b) also shows that CECL-adopting banks originate approximately four times as many auto loans as non-CECL banks. Despite these aggregate differences, the aggregate lending in the auto loan market by CECL and non-CECL adopting banks evolve similarly.

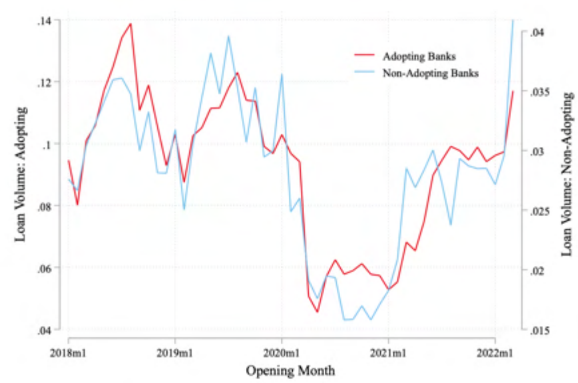
Figure 2: Adopter Bank vs Non-Adopter Bank


(a) Auto Interest Rates


(b) Auto Loan Volumes




(c) Unsecured Interest Rates




(d) Unsecured Loan Volumes

This figure shows the monthly evolution of interest rates and aggregate loan amounts for each type of loan for CECL-adopting banks and non-adopting banks between January 2018 and March 2022. Loan volumes are in billion USD.

The interest rates of personal unsecured installment loans show greater variability than those of auto interest rates. Figure (2c) shows that the average interest rates set by CECL-adopting and non-CECL adopting banks evolved in the same direction during most of the sample period but moved in opposite directions during the initial months of 2020. Finally, figure (2d) shows that the aggregate lending by CECL and non-CECL adopting banks evolve similarly during the sample period despite the fact that CECL-adopting banks originate four times as many personal unsecured installment loans as non-CECL adopting banks.

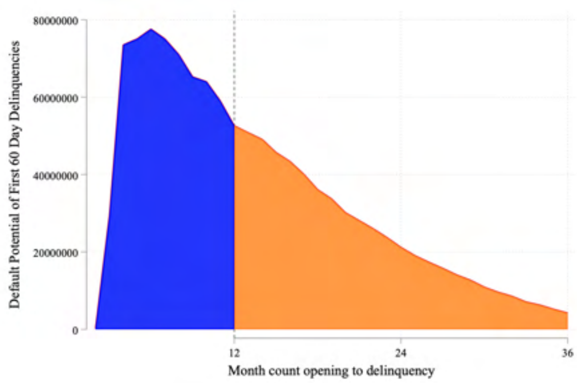
The strong impact that the pandemic had on the interest rates and quantities in the auto and unsecured installment loan markets and the observed differences between the characteristics and market outcomes of CECL and non-CECL adopting banks underscore the need to develop an empirical strategy that isolates the effects of CECL from other potential confounding factors that might affect the evolution of interest rates and quantities during the sample period. Our empirical strategy exploits the idea that, after the transition to the CECL standard, long-term loans became relatively more expensive in terms of capital reserves than similar shorter-term loans because the lifetime probability of default of a longer-term loan is greater than that of a short-term loan. Next, we provide descriptive evidence that the lifetime probability of default increases in a loan's maturity.

Figure 3 plots the aggregate amount of loans within each loan and maturity category that were written-off exactly $n$ months after the loan was originated. Under the IL model, banks provision for loan losses that are expected to emerge over the next twelve months, which are represented by the blue area. The CECL approach, instead, prescribes that banks set provisions for the expected losses over the entire *lifetime* of a loan. Hence, at a loan's origination, banks provision for the lifetime expected losses which are described by the blue and orange areas.

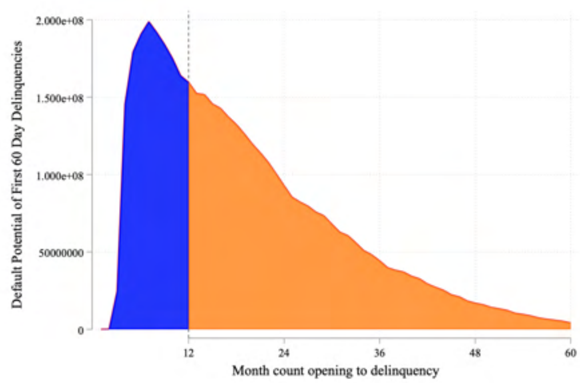
Figures (3a) and (3b) show the total amounts written-off over the lifecycles of 36- and 60-month auto loans, respectively. Both figures indicate that monthly loan write-offs reach their peak prior to these loans' one-year anniversary and slowly decline over the remainder of their lives. These figures also show, nevertheless, that the share of losses occurring more than a year after the origination of the loan (orange area) represents a significant fraction of their lifetime write-offs. Figures (3c) and (3d) exhibit similar patterns for unsecured loans.

To quantitatively evaluate how the share of losses occurring more than a year after the origination

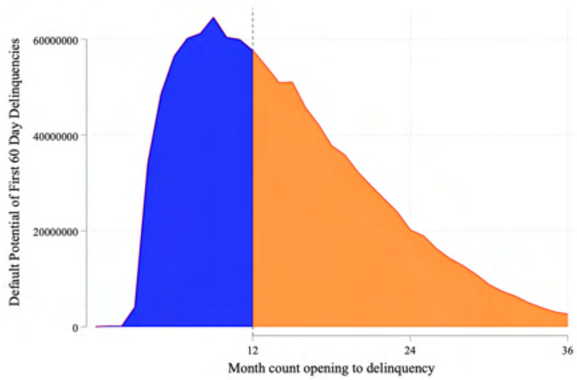
Figure 3: Aggregate loan amounts defaulted after $x$ months by type and maturity



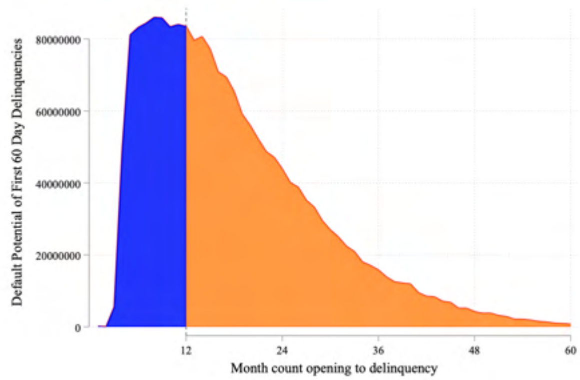

(a) Auto: 36 month loans




(b) Auto: 60 month loans




(c) Unsecured: 36 month loans

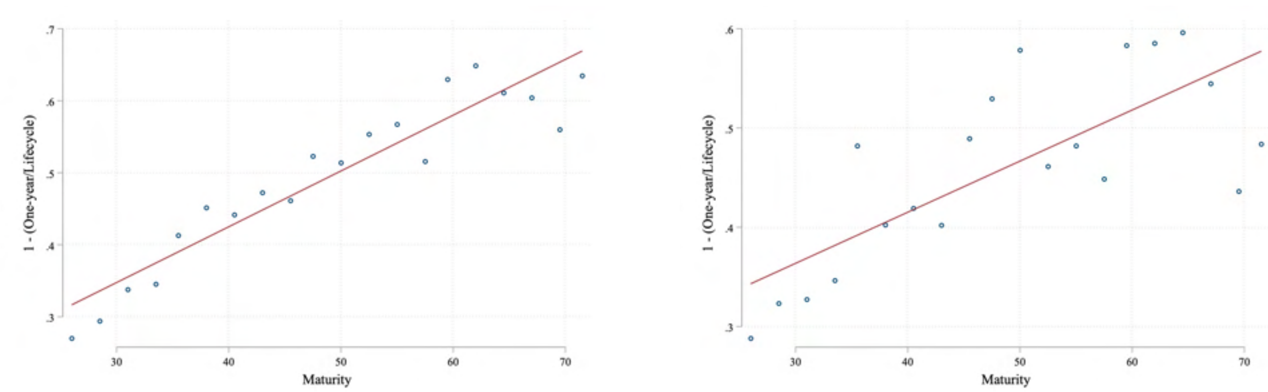



(d) Unsecured: 60 month loans

This figure shows the aggregate outstanding balances of loans with a default in the $x^{th}$ month after origination. Figures (3a) and (3b) show these amounts for the 36-month and 60-month auto loans, respectively. Figures (3c) and (3d) show these amounts for the 36-month and 60-month personal unsecured loans, respectively.

of a loan varies across different loan maturities, we compute the share of lifetime default volume occurring after the first year since loan origination across different loan maturities and we binscatter this share in Figure (4). This figure supports an important premise behind our empirical strategy by showing that the share of write-offs occurring after the first year of a loan increases with a loan's maturity. For instance, the plot of Figure (4a) indicates that 30% of lifetime losses of three-year auto loans occur after the first twelve months since loan inception. When we turn our attention to five-year auto loans, however, we see that the share of lifetime losses occurring after the first year is approximately 60% of lifetime losses. We observe similar patterns for unsecured installment loans in Figure (4b).

Figure 4: Volume defaulting life-cycle vs one year




(a) Auto Loans (b) Unsecured Loans

This figure plots the share of lifetime losses after 12 months since loan inception, $\left(1 - \frac{One\text{-}year}{Lifecycle}\right)$, for each type of maturity for auto loans (Figure 4a) and personal unsecured loans (Figure 4b).

Given that the CECL standard requires banks to set aside reserves for the expected lifetime losses of a loan rather than the expected losses over a one-year horizon, these plots indicate that the adoption of CECL forces banks to set aside greater provisions for loans with longer maturities. Thus, longer-term loans become substantially more expensive from a regulatory capital standpoint.

# 4 Results

## 4.1 Impact on loan interest rates

In this section, we present the results. We begin our analysis by estimating the following difference-in-differences specification:

$$ln(r_{ijtpm}) = \alpha + \beta Post_t \times Treat_j + \delta_{jpm} + \gamma_{ctp} + \theta_{mtp} + \xi_{sbtp} + \epsilon_{ijtpm} \quad (24)$$

where $ln(r_{ijtpm})$ is the natural logarithm of the interest rate for individual $i$ taking a loan from bank $j$, in month $t$, and product $p$ with maturity $m$. We include a battery of fixed effects that allow us to control non-parametrically for a host of factors that might affect the markups, marginal costs, and shadow costs of capital of each bank and confound the estimation of the average treatment effects on the treated. We include bank-product-maturity fixed effects, $\delta_{jpm}$, that absorb invariant differences in the pricing of loans of a certain type and maturity across banks, county-time-product fixed effects, $\gamma_{ctp}$, to absorb spatial differences in the effects of the pandemic and other factors over time that might affect demand and probabilities of default of loan products, product-maturity-time fixed effects, $\theta_{pmt}$, that absorb general trends in the evolution of the interest rates of different products and maturities, and $\xi_{sbtp}$, which is a credit-score bin-time-product fixed effect that absorbs potential differences in the trends across individuals with different credit-score ratings.

Table 2 presents the results of estimating this difference-in-differences specification. In column (1), we report the estimated coefficient associated with the main variable of interest for the pooled sample of loans, whereas in columns (3) and (5) we present results for the auto loan and personal unsecured loan samples, respectively. To address potential concerns that the volatility in credit markets during the spring of 2020 affects our results, we exclude the months of February, March, April, and May of that year in columns (2), (4), and (6). The estimated effects of the adoption of the CECL standard on loan pricing are statistically indistinguishable from zero in five of the six specifications in Table 2. The estimated coefficients obtained using the personal unsecured loan sample in column (5) are slightly more negative than those that we obtain when we use the pooled sample or the auto loan sample in columns (1) and (3).

Table 2: Difference-in-Differences: Impact of CECL adoption on loan interest rates

This table reports coefficients and standard errors from a difference-in-differences specification examining the impact of CECL adoption on loan interest rates. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the interaction between a dummy variable, *Adopter* indicating whether a bank adopted CECL in 2020:Q1 and a dummy variable, *Post*, that takes the value of one after 2020:Q1. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) All | (2) Excl. Corona | (3) All | (4) Excl. Corona | (5) All | (6) Excl. Corona |
| Adopter=1 × post=1 | 0.001 | 0.007 | 0.010 | 0.018 | -0.040* | -0.042 |
| | (0.029) | (0.033) | (0.033) | (0.038) | (0.022) | (0.026) |
| Observations | 2730847 | 2559195 | 2132664 | 1996742 | 598183 | 562453 |
| Adjusted $R^2$ | 0.679 | 0.682 | 0.417 | 0.417 | 0.529 | 0.530 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Bank | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

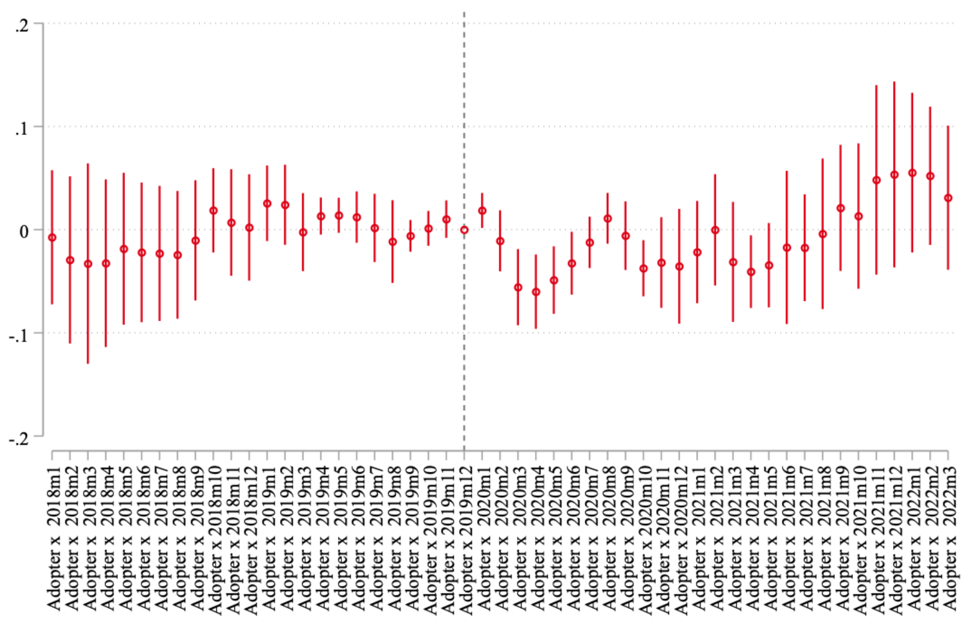
Our difference-in-differences estimates are not simply statistically insignificant with large confidence intervals; rather they are precise zeros. In our pooled sample, the standard error is 0.029, implying that an effect of 5.8 percent would have been detectable at conventional significance levels. By combining our point estimate in column (1) with the respective standard error, we reject that CECL increased loan interest rates by more than 6 percent. The average loan rate in the pooled sample is approximately 6.16%, which suggests that the average loan likely did not see increases of more than 37 basis points as a result of the adoption of the CECL standard.

Next, we expand the specification of equation (24) to include a full set of interactions between month dummies and the indicator variable for CECL adopters:

$$ln(r_{ijtpm}) = \alpha + \sum_{k=-24}^{24} \beta_k 1\{e_t = k\} \times Treat_j + \delta_{jpm} + \gamma_{ctp} + \theta_{mtp} + \xi_{sbtp} + \epsilon_{ijtpm} \tag{25}$$

Figure 5 plots the series of month-by-month coefficients, $\{\beta_k\}$, and respective 95% confidence intervals. We draw two main insights from this figure. First, there are no indications of potential anticipation effects in which CECL adopters adjust the interest rates of their loans months prior to their effective adoption of CECL. Moreover, the plot also suggests that there are no significant differences in the pre-adoption trends of CECL and non-CECL adopters. Following the adoption of

Figure 5: Difference-in-Differences specification: Impact of CECL on loan rates over time




This Figure plots the $\beta_k$ coefficients and respective 95% confidence intervals of a specification similar to that of column (1) of Table 2 using the dynamic difference-in-differences specification in equation (25). Adopters are all banks adopting CECL in January 2020. Standard errors are clustered at the bank level.

the CECL standard, we do not observe sustained effects of the adoption of CECL on loan interest rates in either direction both in the short- and long-run. Having said that, there is a statistically significant dip in the loan rates of adopters relative to loan rates of non-adopters at the onset of the

Covid pandemic. This statistically significant effect of CECL adoption on loan interest rates that occurs only during the months of the pandemic (March-June 2020) could be a symptom that the pandemic had a different effect on the large banks that adopted CECL than it did on other banks that did not adopt CECL.

To address the possibility that the validity of our inferences is affected by shocks that affect CECL and non-CECL banks differently, we implement a triple-differences specification:

$$ln(r_{ijtpm}) = \beta Post_t \times CECL_j \times \left(1 - \frac{oneyear}{lifetime}\right)_{mp} + \eta_{jtp} + \delta_{jpm} + \gamma_{ctp} + \theta_{pmt} + \xi_{sbtp} + \epsilon_{ijtpm}, \quad (26)$$

where $ln(r_{ijtpm})$ is the natural logarithm of the interest rate for individual $i$ taking a loan from bank $j$, in month $t$, and product $p$ with maturity $m$. Our main variable of interest is the triple interaction between an indicator variable for the post-CECL period, $Post$, a variable that indicates whether the bank adopted CECL and, $\left(1 - \frac{oneyear}{lifetime}\right)$, which proxies for $\left(1 - \frac{\delta^1_{Post,l}}{PD_{Post}}\right)$ in the model of section 2.4 and is defined as the share of defaults within each loan type and maturity that occurs after the first twelve months of the loan. Unlike the difference-in-differences specification, we include the bank-time-product fixed effects, $\eta_{jtp}$. These fixed effects are essential to our triple-differences strategy as they allow us to absorb bank-specific time effects that might affect the overall level of interest rates across the products of a bank over time.

The main idea of this specification lies in exploiting variation in the intensity of the impact of CECL across different maturities of loans offered by the same bank so that we can control for potential trends and shocks at the bank level that might affect the overall level of loan rates offered by banks. We present the results of this analysis in Table 3. The main coefficient of interest is the interaction between the post-CECL and CECL adoption dummies and a continuous variable that captures the intensity of the impact of CECL across different types of loans and types of maturities. This coefficient captures the differential effect of CECL adoption on loan rates for a 10 percentage point increase in the share of expected *lifetime* defaults occurring after the first year since loan inception.

Table 3: Triple-Differences: Impact of CECL adoption on loan interest rates

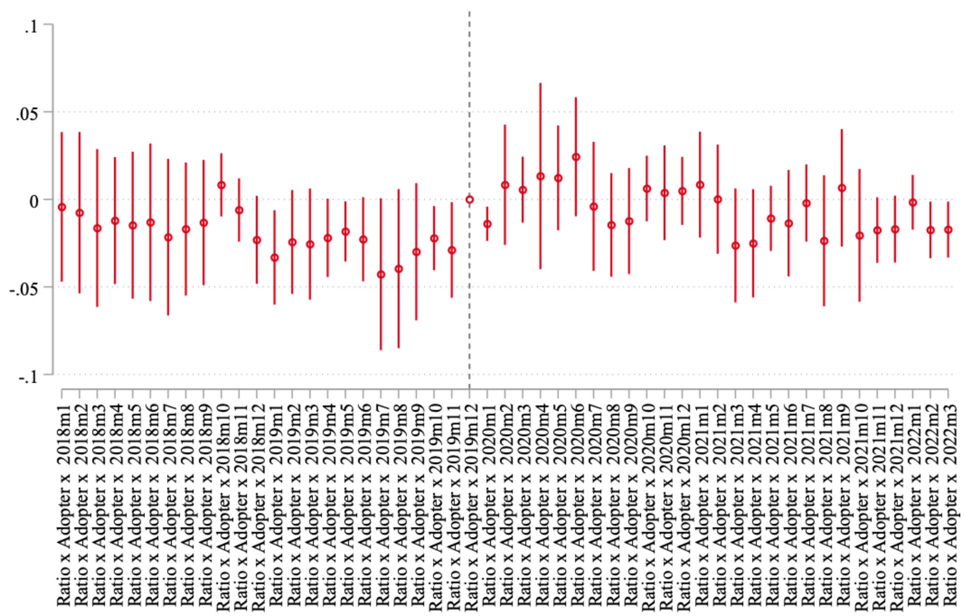
This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan interest rates. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$ ratio, which we define in Table 1 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) All | (2) Excl. Corona | (3) All | (4) Excl. Corona | (5) All | (6) Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | 0.013 | 0.012 | 0.042 | 0.040 | -0.005 | -0.006 |
| | (0.014) | (0.014) | (0.034) | (0.033) | (0.009) | (0.009) |
| Observations | 2578654 | 2414836 | 2001001 | 1871322 | 577653 | 543514 |
| Adjusted $R^2$ | 0.690 | 0.693 | 0.427 | 0.428 | 0.554 | 0.552 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Rssd | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table 3 further support our finding of no statistically or economically significant relationship between CECL adoption and loan rates. A one-standard-deviation increase of approximately 10.97 percentage points in the share of long-term default probability implies an increase in loan rates of 1.4% ($= 0.013 \times 1.097$) with a 95% confidence upper bound for this effect of 4.4% ($= 0.013 \times 1.097 + 1.96 \times 1.097 \times 0.014$). Put differently, our point estimate suggests that a loan with an average interest rate of 6.16% would see an increase in the interest rate of approximately 9 basis points with an upper bound of 28 basis points if its share of long-term default probability, $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right)$, increased by one standard deviation. The estimates using a sample that excludes the months between February and May 2020 are nearly identical. Columns (3) and (5) suggest that the 95% confidence upper bound for auto loans is wider than that for personal unsecured loans. For personal unsecured loans, we can reject modest effects of approximately 2.1% ($= -0.005 \times 1.7 + 1.96 \times 1.7 \times 0.009$) for loans with a one-standard-deviation increase in the share of long-term to short term default probability whereas in the auto loans market our 95% upper bound associated with the impact of one-standard-deviation increase in the impact of CECL is approximately 6.5% ($= 0.042 \times 0.6 + 1.96 \times 0.6 \times 0.034$).

Figure 6: Triple-Differences: Impact of CECL on loan rates over time




This Figure plots the $\beta_k$ coefficients and respective 95% confidence intervals of a specification similar to that of column (1) of Table 3 that expands the analysis to include a full set of interactions between month dummies, the indicator variable for CECL adopters, and the $\left(1 - \frac{One\text{-}year}{Lifecycle}\right) \times 10$ ratio, which we define in Table 1 and multiply by 10 for readability. Standard errors are clustered at the bank level.

Figure 6 plots the series of month-by-month coefficients and respective confidence intervals that we obtained from estimating the triple-differences specification after interacting the main variable of interest with a full set of monthly dummies. The coefficients capture the month-by-month effect on loan rates of a one-standard-deviation increase in our measure of the intensity of the impact of CECL. The results align with those presented in Table 3. In particular, we see that around the transition to CECL there is a slight positive uptick in the interest rates of loans that received a stronger impact from CECL. This effect is, nevertheless, not statistically significant at conventional levels. It is also noteworthy that unlike the difference-in-differences plot of Figure 5, this plot does not show a dip in the estimated coefficients between March 2020 and June 2020. Our interpretation of this result is that the triple-differences specification is able to effectively control for bank-specific shocks that affected the banks' loans interest rates which were also correlated with banks' decisions to adopt the CECL standard.

The model framework that we presented earlier suggests that our main coefficient of interest could be interpreted as suggesting that the shadow cost of the regulatory capital constraint of banks is relatively low. While this interpretation of our results goes against banks' claims that CECL would have an important effect on consumer credit because it would increase their overall cost of capital, it is consistent with evidence from other studies (e.g., Blank et al. [2020]; Li et al. [2020]) suggesting that banks were generally very well-capitalized at the onset of the Covid-19 pandemic. Blank et al. [2020] shows that in the wake of the pandemic, the largest banks in the economy had approximately twice as much capital as they did in the wake of the Global Financial Crisis. The regulatory capital constraint of most banks were thus far from binding which must have eased the pressure that CECL put on capital ratios. Moreover, the Federal Reserve adopted measures designed to promote the conservation of bank capital such as restrictions on capital distributions, changes to the accounting classification of loans as Troubled Debt Restructurings (TDR), and even adjustments to the phase-in period for the regulatory capital effects of CECL.[5]

In Table 4, we further evaluate whether our results become more pronounced when we restrict our attention to a group of banks with below-median levels of capitalization relative to the distribution of Tier 1 capital prior to the adoption of CECL. The results are identical to those of the prior

[5]In Internet Appendix A, we discuss in detail the phase-in rules for the impact of CECL on regulatory capital.

Table 4: Triple-Differences: Impact of CECL adoption on loan interest rates. Banks with below-median Tier 1 Capital

This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan interest rates on the subsample of banks with below-median Tier 1 capital ratios. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$ ratio, which we define in Table 1 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

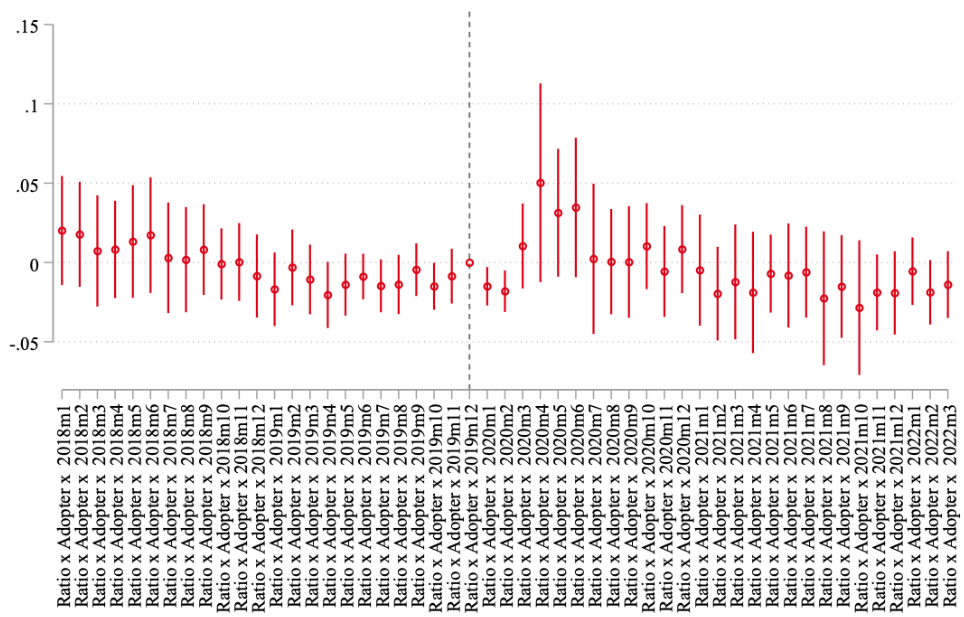
| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Excl. Corona | All | Excl. Corona | All | Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | -0.003 | -0.006 | -0.003 | -0.005 | -0.003 | -0.006 |
| | (0.008) | (0.008) | (0.010) | (0.010) | (0.014) | (0.015) |
| Observations | 1956256 | 1830419 | 1486420 | 1388436 | 469836 | 441983 |
| Adjusted $R^2$ | 0.752 | 0.755 | 0.503 | 0.506 | 0.564 | 0.561 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Bank | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

analyses. We do not find stronger effects of CECL adoption on interest rates for banks with lower levels of regulatory capital and, if anything, our estimates are more precisely estimated null effects. In particular, the 95% upper bound for the effect of a one-standard-deviation increase in the intensity of CECL is an increase in the loan interest rates of 1.4%. The plot of Figure 7 further suggests that the estimated effects of the adoption of the CECL standard are not more pronounced in the subset of banks with lower levels of regulatory capital across most months of the post-CECL period. A possible interpretation of this result is that even low-tier 1 capital banks had relatively abundant levels of regulatory capital by historical standards and thus not even these banks had to adjust their loan rates to take into account their capital impact. We caution, however, that the capital structure of a bank is a highly endogenous object, which might also explain why we fail to observe significant effects of CECL adoption on interest rates in this subset of banks.

We conduct extensive sensitivity analyses to assess the robustness of the main analysis to alternative variable definitions and specifications. In the Internet Appendix B we evaluate the

Figure 7: Triple-Differences: Impact of CECL on loan rates over time. Bank with below-median Tier 1 Capital




This Figure plots the $\beta_k$ coefficients and respective 95% confidence intervals of a specification similar to that of column (1) of Table 4 that expands the analysis to include a full set of interactions between month dummies, the indicator variable for CECL adopters, and the $\left(1 - \frac{One\text{-}year}{Lifecycle}\right) \times 10$ ratio, which we define in Table 1 and multiply by 10 for readability. Standard errors are clustered at the bank level.

robustness of our triple-differences design results to alternative procedures to compute the share of defaults that occur one year after the origination of the loan. Specifically, we evaluate whether the empirical results are similar when we restrict the sample that we use to compute these default shares to (i) loans that expired by the end of 2019 and (ii) to loans that expired prior to 2019 and belong to a balanced cohort of loans.

In the Internet Appendix C, we evaluate whether our results are robust to using an alternative dataset. In particular, we use bank-level interest rates for auto loans across different maturities that we obtain from RateWatch. RateWatch surveys over 100,000 bank branches weekly and collects advertised interest rates for new loans and the data set covers a large percentage of all banks in the United States. We obtained information on the advertised loan rates of new- and used-car loans for 36, 48, 60, and 72 month maturities and use these data to examine if the difference between the auto loan rates of long- and short-term loans of CECL banks were relatively more affected than the same difference for banks that did not adopt CECL. Consistent with our main findings, the results we present in the Internet Appendix C suggest that the adoption of CECL did not increase the spread between the rates of long- and short-term auto loans of CECL adopting banks relative to those of non-CECL adopting banks.

## 4.2 Impact on loan amounts

A potential explanation for our results in the previous section is that banks do not change their loan pricing practices but rather opt to ration loan amounts in response to the additional provision surcharges associated with CECL. In this section, we examine this possibility by implementing an identical triple-differences empirical specification to evaluate if the relative difference between the average size of long- and short-term loans offered by CECL-adopting banks declined relative to the same difference for non-adopting banks.

We present our results in Table 5. The results further support our findings that the effects of CECL adoption on the provision and regulatory capital charges associated with each type of loan likely had weak effects on banks' overall real-lending decisions. The findings in Table 5 suggest that, if anything, the average loan size of a long-term relative to a short-term loan originated by CECL banks increased by approximately 1.4% relative to the same relative difference for non-CECL adopters.

Table 5: Triple-Differences: Impact of CECL on loan amounts

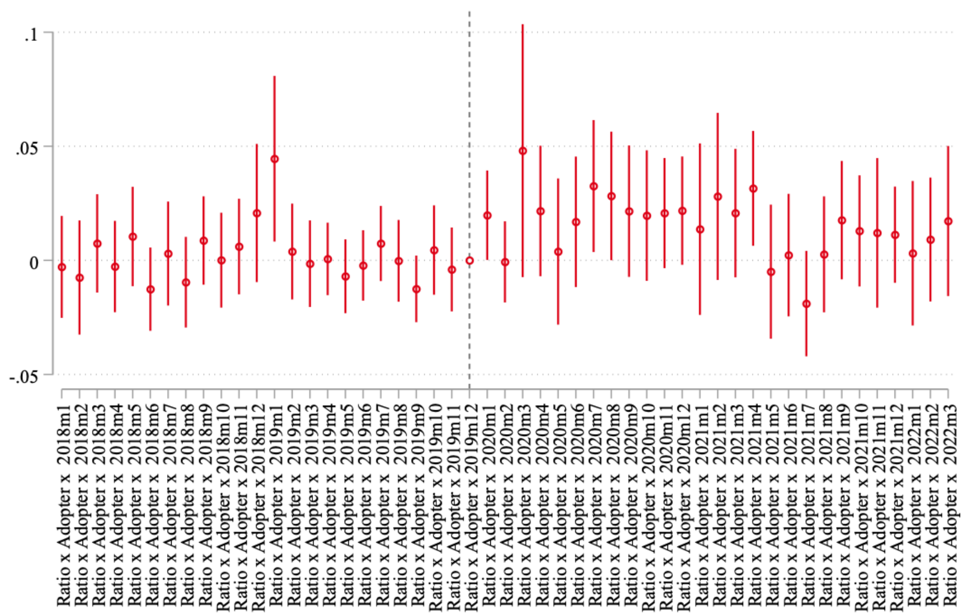
This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan amounts. The dependent variable is the natural logarithm of the loan amounts on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$ ratio, which we define in Table 1 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Excl. Corona | All | Excl. Corona | All | Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | 0.013* | 0.012* | 0.017 | 0.016 | 0.010 | 0.009 |
| | (0.007) | (0.006) | (0.013) | (0.013) | (0.008) | (0.007) |
| Observations | 2672898 | 2500098 | 2092326 | 1953794 | 580572 | 546304 |
| Adjusted $R^2$ | 0.655 | 0.658 | 0.367 | 0.367 | 0.638 | 0.641 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Bank | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Figure 8 traces the impact of CECL adoption on average loan sizes over time using a triple-differences specification. The results of this analysis further suggest that average loan sizes are not strongly affected by the adoption of CECL. Thus, banks do not seem to have shifted their portfolio toward shorter-term loans by rationing loan amounts on longer-term loans.

Figure 8: Triple-Differences: Impact of CECL adoption on loan amounts over time




This figure plots the $\beta_k$ coefficients and respective 95% confidence intervals of a specification similar to that of column (1) of Table 5 that expands the analysis to include a full set of interactions between month dummies, the indicator variable for CECL adopters, and the $\left(1 - \frac{One\text{-}year}{Lifecycle}\right) \times 10$ ratio, which we define in Table 1 and multiply by 10 for readability. Standard errors are clustered at the bank level.

# 5 Conclusion

The recent adoption of the CECL standard has raised considerable debate among financial institutions, accountants, public officials, and academics about the potential effects of CECL on banks' regulatory capital and lending. One of the most heated areas of debate has been whether the adoption of CECL might have heterogeneous effects across certain types of loans. In particular, there has been considerable debate (e.g., Hashim et al. [2022]) about the expected lifetime losses aspect of the implementation of CECL in the United States, which forces banks to make greater upfront loss reserves for longer-term loans higher relative to shorter-term loans. Using granular data from TransUnion, we conduct an initial investigation of whether the adoption of CECL has had an effect on banks' lending and prices. Contrary to widely-held concerns in practitioner circles that the adoption of CECL will have heterogeneous effects on different types of lending (e.g., Treasury Department [2020]; Killian and Ding [2020]), we do not find significant effects of the adoption of CECL on the pricing and quantities of loans whose loss reserves that were more strongly affected by the CECL standard. We believe that these findings have important implications for the ongoing policy evaluation of the impact of CECL.

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# Internet Appendix

## A CECL Transition and Capital Relief During Covid

Our model posits that CECL operates by imposing higher capital requirements and thereby increasing regulatory capital constraints. However, during the Covid-19 pandemic, the OCC, Federal Reserve, and FDIC updated their CECL guidance providing regulatory capital relief. Those relief measures were introduced to "allow banking organizations to better focus on supporting lending to creditworthy households and businesses."[6] In March 2020, the agencies published the Interim Final Rule, which largely remained unchanged and was published as Final Rule in August 2020.[7] In particular, the final rule provided the option of a five year transition period delaying the effect of CECL on regulatory capital by two years. Nevertheless, we argue that CECL affected regulatory capital and, in particular, that the triple difference design described in Section 2.4 is especially suitable to tease out CECL effects. This section has two parts. First, we describe the capital relief provided by the final rule.[8] Second, we argue that the applied design is particularly suitable to pick up capital effects present during the relief period.

The Final Rule delays the regulatory capital effect of the day one CECL adoption by two years. Instead of a three-year transition period, banks can elect to apply a five-year transition period where the day-one effect starts to be phased-in in the third year (with 25%). In the fourth and fifth years, the relief is reduced by an additional 25 percentage points. In addition to the day-one effect, the regulation applies a uniform approach to approximate the effect of CECL in the first two years after adoption. In an ideal world without the cost of maintaining provisioning systems, regulators would

[6] https://www.govinfo.gov/content/pkg/FR-2020-03-31/pdf/2020-06770.pdf

[7] Interim Final Rule March 2020 and Final Rule August 2020

[8] We ignore transition rules for deferred tax assets for the sake of clarity of this section.

allow banks to maintain an incurred and expected loss provisioning system and use ILM provisions for capital ratio calculations. However, this approach is prohibitively costly and would essentially require maintaining two separate systems with all associated internal control measures. Instead, the rule mitigates the CECL impact by applying a 0.25 factor to increases in Allowances for Loan Losses under CECL. This uniform mitigation measure is locked-in after two years and phased in jointly with the day-one effects over the subsequent three years. Hence, regulatory capital relief due to the Covid-19 pandemic is:

$$\begin{aligned} \text{Capital Relief} = & \ (\text{Starting ALL Post CECL} - \text{Ending ALL Pre CECL}) \\ & + 0.25 * (\text{Ending ALL Post CECL} - \text{Starting ALL Post CECL}) \end{aligned} \tag{27}$$

As a result, 75% of the CECL effect remains for newly issued loans. A concern here is that 75% of CECL provisions are not too different from the provision required by an incurred loss model. However, we should note two facts (1) The relief does not address differential timing of provisioning under ILM and CECL such that capital constraints may be tighter under CECL due to faster loss provisioning (2) the uniform CECL haircut is a one-size-fits all policy maintaining CECL differences for long and short loan products. Hence, even in a case with small overall capital constraint differences across ILM and CECL banks, long loans are still relatively more expensive for CECL-adopting banks than for ILM banks. For example, consider a 20,000 USD loan with expected life-time default of 600 USD. Then expected one-year default is roughly 240 USD (=1/2.5 * 600). Hence, under ILM, provisioning for this loan would be 240 USD, while under the modified capital relief, the bank still has to provision 75% of the 600 USD expected life-time loss, 450 USD. Hence, longer loans still require more loss provisioning. Our triple-difference design picks up exactly this capital cost variation for long and short rates across ILM and CECL banks.

# B Robustness default ratio computation

In this section, we evaluate the robustness of our main result to the computation of the historical default shares. In the main paper, we compute historical default rates as the average default volumes over one year vs. loan lifetime of all loans originated from 2009 to 2019 only using default information realized by the end of 2019. However, banks may compute historical default rates only taking expired loans into account. Hence, we first compute maturity-specific historical default rates for loans that expired by the end of 2019 only. Second, we further restrict the set of loans to compute historical default rates by requiring (1) that all loans are expired by the end of 2019 and (2) that all loans used for historical default computation are of the same vintage. That is, because 7-year loans expiring by the end of 2019 must have been issued in or before 2012, we neither use short-term loans issued after 2012. These restrictions primarily affect the computation of the share of defaults after the first year since loan origination, $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right)$. However, our conclusions from the main text remain unchanged.

## B.1 Only expired historical loans

In this section, we compute historical default rates using expired loans only. In particular, we restrict the set of loans to loans that expired by the end of 2019. We then compute the historical default volumes for one-year since loan origination and historical default volumes over the entire loan lifetime. We then repeat the analysis of the main text. Table B.1 provides summary statistics and corresponds to Table 1 in the main text. The share of long-term defaults here is higher than in the main text. The average ratio $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right)$ increases from 0.61 to 0.7 for auto loans and the standard deviation increases from 0.06 to 0.08. Those increases are mechanical effects arising from reduced loan lifetime default censoring. Since all loans are expired in this sample, there is no censoring of the observed historical default volumes for long-term loans issued close to 2019. The correct choice of lifetime default computations depends on the specific methodology banks employ when computing historical default rates. If banks utilize their entire historical portfolio, including currently outstanding loans, then the methodology of the main text is appropriate. If banks exclude currently outstanding loans in their historical default computations, then the methodology of this section is more appropriate. Regardless, we will argue that the conclusions do not change. We can observe a similar increase for unsecured loans from 0.48 in the main text to 0.52 in Table B.1 and an unchanged standard deviation of 0.17.

Table B.1: Summary statistics: Matured by 2019

| | Count | Mean | Sd | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| *Panel A: Auto* | | | | | | |
| Interest Rate | 2,123,380 | 0.05 | 0.02 | 0.03 | 0.05 | 0.06 |
| Loan Amount | 2,123,380 | 26,421 | 11,745 | 17,495 | 25,000 | 34,184 |
| Credit Score | 2,123,380 | 736 | 66 | 690 | 746 | 792 |
| $1-\frac{One-year}{Lifecycle}$ | 2,123,380 | 0.70 | 0.08 | 0.68 | 0.74 | 0.74 |
| Maturity | 2,123,380 | 5.63 | 1.04 | 5.00 | 6.00 | 6.00 |
| Adopter | 2,123,380 | 0.79 | 0.40 | 1.00 | 1.00 | 1.00 |
| *Panel B: Unsecured* | | | | | | |
| Interest Rate | 617,981 | 0.12 | 0.04 | 0.09 | 0.11 | 0.14 |
| Loan Amount | 617,981 | 12,185 | 9,003 | 5,000 | 10,000 | 18,000 |
| Credit Score | 617,981 | 712 | 66 | 668 | 719 | 760 |
| $1-\frac{One-year}{Lifecycle}$ | 617,981 | 0.52 | 0.17 | 0.57 | 0.57 | 0.60 |
| Maturity | 617,981 | 3.78 | 1.47 | 3.00 | 4.00 | 5.00 |
| Adopter | 617,981 | 0.71 | 0.45 | 0.00 | 1.00 | 1.00 |

This table provides descriptive statistics of the main variables in the empirical analysis. $\left(1-\frac{One\text{-}year}{Lifecycle}\right)$ is one minus the ratio between the average probability of default in the first year and the lifetime probability of default for each type and maturity of loan. This ratio is computed using pre-CECL data only using loans that expired by the end of 2019. We provide definitions of the remaining variables in Table 1 of the main document. Source: TransUnion.

Table B.2 repeats the analysis of Table 3 in the main text. the coefficient of interest is the interaction between the post-CECL and CECL adoption dummies and the continuous variable capturing the intensity of the CECL impact across different loan types. This coefficient captures the differential effect of CECL adoption on loan rates for a 10 percentage point increase in the share of expected *lifetime* defaults occurring after the first year since loan inception. Column (1) finds an insignificant increase in interest rates of 2.0% ($= 0.015 \times 1.31$) for a one-standard-deviation increase in the share of long-term defaults, $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$. The 95% confidence band upper bound for a one-standard-deviation increase in the share of long-term defaults is economically small at 5.3% ($= 0.015 \times 1.31 + 1.96 \times 1.31 \times 0.013$) and almost identical to the finding in the main text.

Table B.2: Triple-Differences: Impact of CECL adoption on loan interest rates: Matured by 2019

This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan interest rates. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$ ratio, which we define in Table B.1 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Excl. Corona | All | Excl. Corona | All | Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | 0.015 | 0.014 | 0.032 | 0.031 | -0.001 | -0.003 |
| | (0.013) | (0.013) | (0.025) | (0.025) | (0.007) | (0.007) |
| Observations | 2578654 | 2414836 | 2001001 | 1871322 | 577653 | 543514 |
| Adjusted $R^2$ | 0.690 | 0.693 | 0.427 | 0.428 | 0.554 | 0.552 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Rssd | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Again we restrict the set of adopters to those with below median tier 1 capital ratio. Table B.3 corresponds to Table 4 in the main text. Similar to the main text, we do not find that results are more pronounced in the set of below-median tier 1 capital banks. If anything, we find more precisely estimated nulls. The 95% confidence band upper bounds for a one standard deviation increase in the share of long-term defaults is 1.5% ($= 0.000 * 1.31 + 1.96 * 1.31 * 0.006$).

Table B.3: Triple-Differences: Impact of CECL adoption on loan interest rates. Banks with below-median Tier 1 Capital: Matured by 2019

This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan interest rates on the subsample of banks with below-median Tier 1 capital ratios. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1 - \frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$ ratio, which we define in Table B.1 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

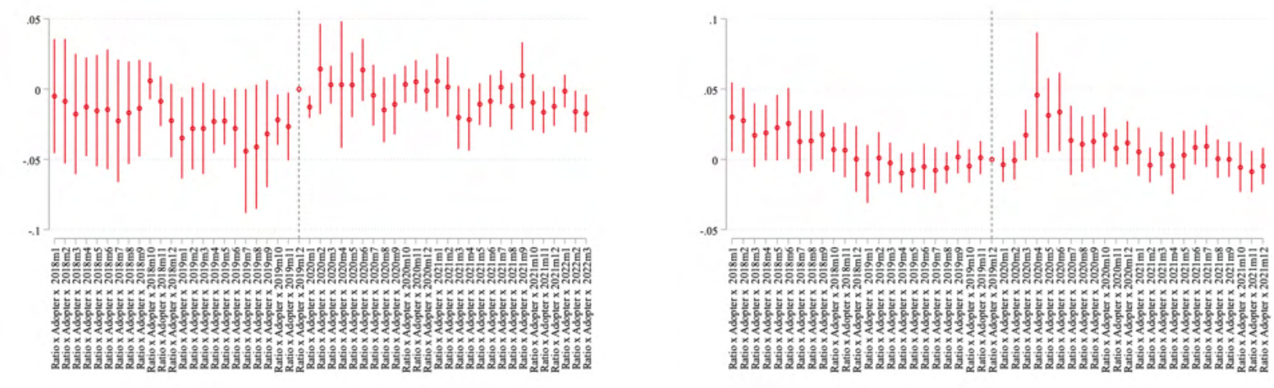
| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Excl. Corona | All | Excl. Corona | All | Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | 0.000 | -0.002 | -0.001 | -0.003 | 0.003 | -0.000 |
| | (0.006) | (0.006) | (0.008) | (0.007) | (0.012) | (0.013) |
| Observations | 1956256 | 1830419 | 1486420 | 1388436 | 469836 | 441983 |
| Adjusted $R^2$ | 0.752 | 0.755 | 0.503 | 0.506 | 0.564 | 0.561 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Bank | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Figure B.1 plots the dynamics of the above specifications by interacting monthly dummies with the adopter dummy and share of long-term defaults. The patterns are similar to the patterns in the main text.

Figure B.1: Triple difference dynamics

This Figure plots the $\beta_k$ coefficients and respective 95% confidence intervals of a specification similar to that of column (1) of Tables B.2 and B.3 that expands the analysis to include a full set of interactions between month dummies, the indicator variable for CECL adopters, and the $\left(1 - \frac{One\text{-}year}{Lifecycle}\right) \times 10$ ratio, which we define in Table B.1 and multiply by 10 for readability. Standard errors are clustered at the bank level.




(a) All

(b) Low Tier 1

## B.2 Only expired historical loans of the same vintage

In this section, we further restrict the set of loans used to compute historical default volumes. In addition to requiring that all loans are expired by the end of 2019, we also require that loans of the same product are of the same vintage. That is, because seven-year auto loans issued in 2013 do not expire by the end of 2019, we neither use six-year auto loans issued in 2013 for default rate computations. This ensures that differences in the lifetime default rates relative to the one-year default rates are not driven by different issuing dates for different maturities. However, our conclusions remain unchanged from the main text.

Table B.4: Summary statistics: Matured by 2019 and same vintage

| | Count | Mean | Sd | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| *Panel A: Auto* | | | | | | |
| Interest Rate | 2,123,380 | 0.05 | 0.02 | 0.03 | 0.05 | 0.06 |
| Loan Amount | 2,123,380 | 26,421 | 11,745 | 17,495 | 25,000 | 34,184 |
| Credit Score | 2,123,380 | 736 | 66 | 690 | 746 | 792 |
| $1 - \frac{One\text{-}year}{Lifecycle}$ | 2,123,380 | 0.71 | 0.08 | 0.70 | 0.76 | 0.76 |
| Maturity | 2,123,380 | 5.63 | 1.04 | 5.00 | 6.00 | 6.00 |
| Adopter | 2,123,380 | 0.79 | 0.40 | 1.00 | 1.00 | 1.00 |
| *Panel B: Unsecured* | | | | | | |
| Interest Rate | 617,981 | 0.12 | 0.04 | 0.09 | 0.11 | 0.14 |
| Loan Amount | 617,981 | 12,185 | 9,003 | 5,000 | 10,000 | 18,000 |
| Credit Score | 617,981 | 712 | 66 | 668 | 719 | 760 |
| $1 - \frac{One\text{-}year}{Lifecycle}$ | 617,981 | 0.50 | 0.15 | 0.51 | 0.56 | 0.58 |
| Maturity | 617,981 | 3.78 | 1.47 | 3.00 | 4.00 | 5.00 |
| Adopter | 617,981 | 0.71 | 0.45 | 0.00 | 1.00 | 1.00 |

This table provides descriptive statistics of the main variables in the empirical analysis. $\left(1 - \frac{One\text{-}year}{Lifecycle}\right)$ is one minus the ratio between the average probability of default in the first year and the lifetime probability of default for each type and maturity of loan. This ratio is computed using pre-CECL data only using loans that expired by the end of 2019 and have the same vintage. We provide definitions of the remaining variables in Table 1 of the main document. Source: TransUnion.

Table B.4 provides summary statistics and corresponds to Table 1 in the main text. For auto loans, the share of defaults occurring after the first year since loan origination is 71% reflected by the average ratio $\left(1-\frac{\textit{One-year}}{\textit{Lifecycle}}\right)$ of 0.71. The standard deviation of the long-term default share is also increased at 0.08 relative to the main text. For unsecured loans, the share of long-term defaults is 0.5, which reflects a modest increase relative to the main text but is lower in comparison to Table B.1. The standard deviation of the long-term default share is lower than in the main text and in the previous section at 0.15.

Table B.5 repeats the analysis of Table 3 in the main text. Column (1) finds an insignificant increase in interest rates of 2.2% ($= 0.016 \times 1.35$) for a one-standard-deviation increase in the share of long-term defaults, $\left(1-\frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$. The 95% confidence band upper bound for a one-standard-deviation increase in the share of long-term defaults is economically small at 5.9% ($= 0.016 * 1.35 + 1.96 * 1.35 * 0.014$) and similar to the finding in the main text.

Table B.5: Triple-Differences: Impact of CECL adoption on loan interest rates: Matured by 2019 and same vintage

This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan interest rates. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1-\frac{\textit{One-year}}{\textit{Lifecycle}}\right) \times 10$ ratio, which we define in Table B.4 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Excl. Corona | All | Excl. Corona | All | Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | 0.016 | 0.015 | 0.029 | 0.028 | -0.004 | -0.005 |
| | (0.014) | (0.014) | (0.023) | (0.023) | (0.008) | (0.008) |
| Observations | 2578654 | 2414836 | 2001001 | 1871322 | 577653 | 543514 |
| Adjusted $R^2$ | 0.690 | 0.693 | 0.427 | 0.428 | 0.554 | 0.552 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Rssd | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Similar to the main analysis, we also restrict treated banks to banks with below median tier 1 capital ratio and reestimate the triple difference specification. Table B.6 shows the results of this analysis. Again, we find more precisely estimated nulls. Column (1) shows a point estimate close to zero. Combining point estimate and standard errors, the upper bound of the 95% confidence band for a one-standard deviation increase in the share of defaults occurring one year after loan origination corresponds to a 1.3% ($= -0.002 * 1.35 + 1.96 * 1.35 * 0.006$) increase in interest rates.

Table B.6: Triple-Differences: Impact of CECL adoption on loan interest rates. Banks with below-median Tier 1 Capital: Matured by 2019 and same vintage

This table reports coefficients and standard errors from a triple-differences specification examining the impact of CECL adoption on loan interest rates on the subsample of banks with below-median Tier 1 capital ratios. The dependent variable is the natural logarithm of the implied interest rate on each individual loan. The main variable of interest is the triple interaction between a dummy variable, *Adopter*, indicating whether a bank adopted CECL in 2020:Q1, another dummy variable, *Post*, that takes the value of one after 2020:Q1, and the $\left(1 - \frac{One\text{-}year}{Lifecycle}\right) \times 10$ ratio, which we define in Table B.4 and multiply by 10 for readability. Columns (2), (4), (6) exclude the months of February, March, April, and May of 2020.

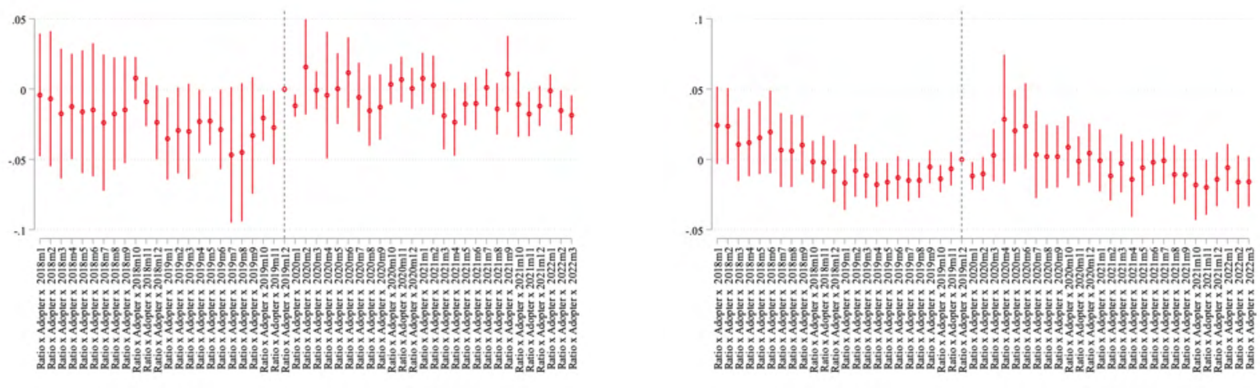
| | All | | Auto | | Unsecured | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | All | Excl. Corona | All | Excl. Corona | All | Excl. Corona |
| Adopter=1 × post=1 × 1-(One-Year/Lifetime) | -0.002 | -0.004 | -0.002 | -0.003 | -0.002 | -0.004 |
| | (0.006) | (0.006) | (0.007) | (0.007) | (0.014) | (0.015) |
| Observations | 1956256 | 1830419 | 1486420 | 1388436 | 469836 | 441983 |
| Adjusted $R^2$ | 0.752 | 0.755 | 0.503 | 0.506 | 0.564 | 0.561 |
| Bank x Maturity x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| County x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Maturity x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Score Bucket x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank x Month x Product FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster | Bank | Bank | Bank | Bank | Bank | Bank |

Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Figure B.2 plots the dynamics of the above specifications by interacting monthly dummies with the adopter dummy and share of long-term defaults. The patterns are similar to the patterns in the main text.

## Figure B.2: Triple difference dynamics

This Figure plots the $\beta_k$ coefficients and respective 95% confidence intervals of a specification similar to that of column (1) of Tables B.5 and B.6 that expands the analysis to include a full set of interactions between month dummies, the indicator variable for CECL adopters, and the $\left(1 - \frac{One\text{-}year}{Lifecycle}\right) \times 10$ ratio, which we define in Table B.4 and multiply by 10 for readability. Standard errors are clustered at the bank level.



(a) All (b) Low Tier 1

# C RateWatch

In this section, we check the robustness of our main conclusions and repeat the analysis using the RateWatch data. We delegate this analysis to the appendix and focus on credit bureau data in the main analysis for several reasons. First, credit bureau data is at the loan level and, therefore, allows controlling for credit quality and local lending conditions by including a battery of fixed effects. Second, by exploiting loan-level data we obtain an accurate representation of the credit market, whereas the analysis conducted in this section has to pool rates at the lender level. Nevertheless, we show that the conclusions exploiting new auto rates posted by banks are not substantially different from our main analysis.

Figure C.1 shows that the aggregate rate development is comparable to Figure 1a in our main analysis. A small increase in average rates is followed by a decline in average rates from 2019 onwards. Rate differences and the higher volatility of interest rates likely arise from different rate weighting across the two datasets. While each bank is equally weighted in this Appendix section, banks with more loans receive higher weight in the main analysis as they make more loans.

Table C.1 provides summary statistics for the RateWatch sample. Observations are at a bank-month level for the period from 2018 to 2021. Average interest rates range between 4.5 and 5%. Due to the bank-month observation level, the share of observations for CECL Adopters is substantially lower than in our main dataset at the loan level. Similarly, the share of observations post CECL adoption is lower. Bank size at the beginning of 2018 exhibits substantial right skew - while the average bank size is 10 billion USD, the median bank size is only 465 million USD. Considering the hypothesized channel for CECL effects relying on capital constraints, it is noteworthy that the average bank is well capitalized at the beginning of 2018 with average Tier 1 capital ratios exceeding 15%. Hence, small or zero CECL effects may be due to good bank capitalization and low shadow cost of capital.

Figure C.1: Rates over time RateWatch 2018-2021

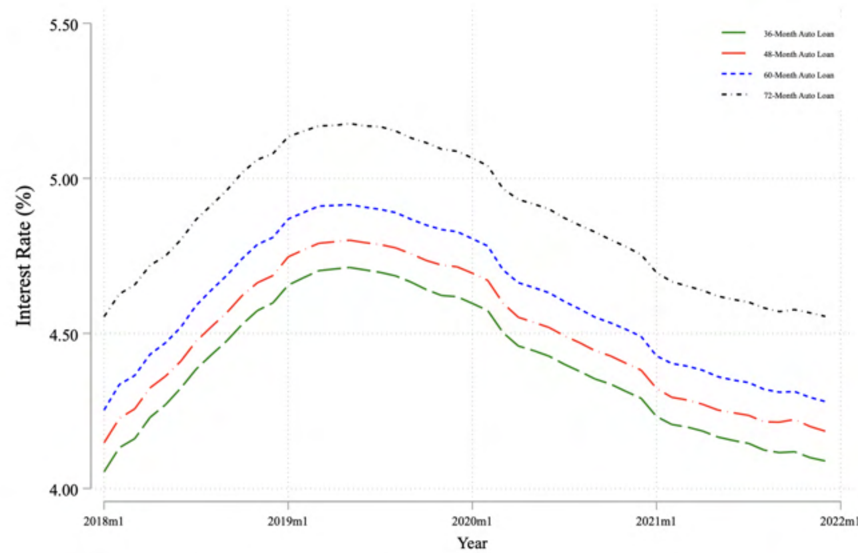



Table C.1: Summary Statistics RateWatch 2018-2021

| | count | mean | sd | p10 | p25 | p50 | p75 | p90 |
|---|---|---|---|---|---|---|---|---|
| 36-month new car loan | 58,282 | 4.71 | 1.15 | 3.40 | 3.95 | 4.50 | 5.40 | 6.25 |
| 48-month new car loan | 58,254 | 4.81 | 1.16 | 3.49 | 3.99 | 4.69 | 5.50 | 6.44 |
| 60-month new car loan | 58,333 | 4.92 | 1.17 | 3.50 | 4.00 | 4.75 | 5.50 | 6.50 |
| 72-month new car loan | 38,843 | 4.88 | 1.04 | 3.74 | 4.20 | 4.75 | 5.50 | 6.25 |
| Adopter | 58,611 | 0.10583 | 0.30763 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 1.00000 |
| Post CECL Adoption | 58,611 | 0.04429 | 0.20574 | 0.00000 | 0.00000 | 0.00000 | 0.00000 | 0.00000 |
| Total Assets Beginning 2018 | 961 | 10191397 | 109103586 | 106383 | 217674 | 464823 | 1216456 | 4284334 |
| Tier 1 ratio Beginning 2018 | 961 | 15.21 | 5.50 | 10.91 | 11.86 | 13.58 | 16.89 | 21.13 |

Next, we estimate a difference-in-difference specification where the outcome variable is the log difference between long and short interest rates. We define 36-month auto loan rates as the short interest rate and vary long rates across specifications. In columns (1) and (2) of Table C.2, the long rates are 48-month auto loan rates, and the outcome variable is $ln(r_{j,t,48}) - ln(r_{j,t,36})$. Columns (3) to (4) and (5) to (6) show results for 60 and 72-month as long auto loan rates, respectively. As the duration spread between long and short rates increases, our theory predicts that the effect size should increase from columns (2) to (4) and (6). While the point estimate does indeed increase, non of the specifications is statistically or economically significant, validating our conclusions from the main text. The CECL effect on interest rates appears to be modest at most.

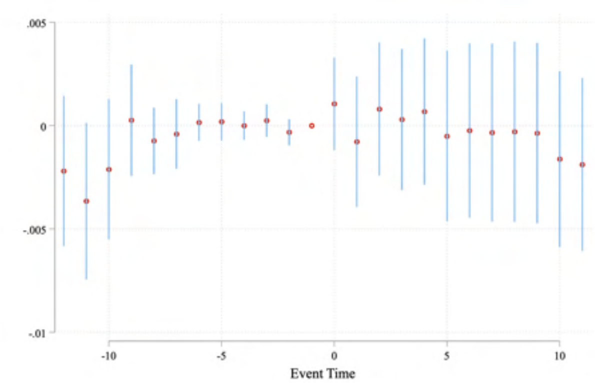
Table C.2: Stacked Regressions RateWatch

| | $ln(r_{j,t,48}) - ln(r_{j,t,36})$ | | $ln(r_{j,t,60}) - ln(r_{j,t,36})$ | | $ln(r_{j,t,72}) - ln(r_{j,t,36})$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post x CECL | -0.001 | 0.001 | 0.001 | 0.002 | 0.003 | 0.003 |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.004) | (0.004) |
| Observations | 150264 | 149808 | 150912 | 150456 | 100801 | 100057 |
| Adjusted $R^2$ | 0.879 | 0.879 | 0.908 | 0.907 | 0.911 | 0.911 |
| Rssd x Group FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month x Group FE | Yes | No | Yes | No | Yes | No |
| State x Month x Group FE | No | Yes | No | Yes | No | Yes |
| Cluster | State x Group | State x Group | State x Group | State x Group | State x Group | State x Group |

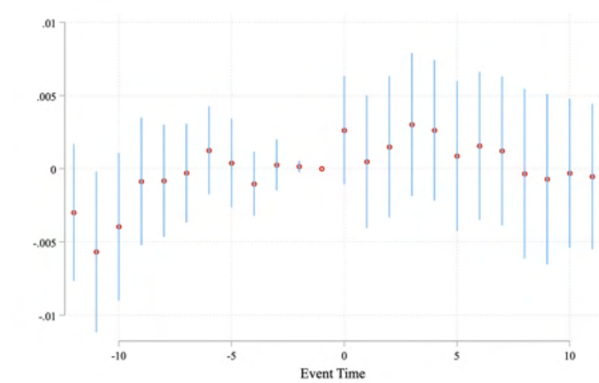
Standard errors in parentheses
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

To evaluate the dynamic effects of CECL adoption that may be masked in the table, we implement a dynamic difference-in-difference specification and plot the coefficients on the relative time dummies interacted with the CECL adoption dummy. Estimates are relative to the month prior to CECL adoption. Figure C.2 shows results for the three different rate spreads as outcome variables. The implemented specifications are essentially equivalent to columns (2), (4), and (6) of Table C.2. All panels of Figure C.2 show largely flat dynamic estimates confirming the results of Table C.2.

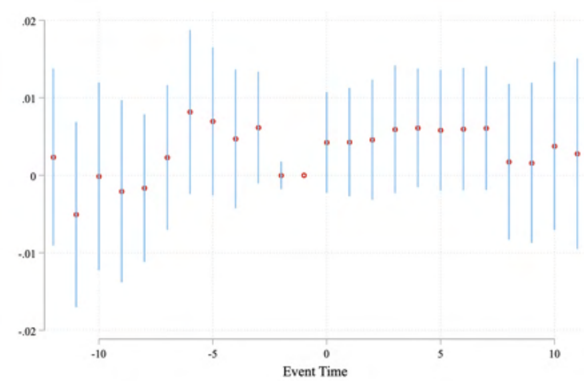
Figure C.2: Dynamic specification




(a) $ln(r_{j,t,48}) - ln(r_{j,t,36})$




(b) $ln(r_{j,t,60}) - ln(r_{j,t,36})$




(c) $ln(r_{j,t,72}) - ln(r_{j,t,36})$