WORKING PAPER · NO. 2025-102

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AUGUST 2025 (UPDATED DECEMBER 2025)

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December 23, 2025

Abstract

We investigate whether trust plays a significant role in retail borrowers' decisions to transact with banks. We use bank enforcement actions publicized in the local news media as a reputational shock that undermines consumers' trust in banks. Survey data indicate that enforcement actions are associated with significant declines in trust in banks and bankers. Using granular loan data from TransUnion that links retail borrowers to banks, we find that higher-quality borrowers exit sanctioned banks. These effects are not present prior to the enforcement action. Consistent with declining trust in the banking system, higher-quality borrowers leave not only sanctioned banks but also unsanctioned banks with exposure to sanctioned banks, migrating instead to nonbank financial institutions. Sanctioned banks have fewer repeat borrowers, and the shift towards lower-quality borrowers is more pronounced with declining survey-based trust measures and negative local news coverage. In contrast, borrower quality shows little change when local news is positive or conveys trust and in regions without local news outlets, underscoring the crucial role of the news media in contextualizing news and shaping consumers' trust in banks. Additional tests reveal these findings are inconsistent with supply-side changes.

JEL Classifications: D12, E21, G20, G21, G38, M4, R22
Keywords: Banking, Bank supervision, Consumer credit, Default, Delinquency, Enforcement actions, News deserts, Reputational costs, TransUnion, Trust in banks

*We appreciate helpful comments from Karthik Balakrishnan, Phil Berger, Jonathan Craske, Urooj Khan, Maria Khrakovsky, Frederik Kohl, Jung Koo Kang, Laurel Mazur, Fabian Nagel, Raghuram Rajan, Vidhya Soundararajan, Jing Wen, Billy Xu, and seminar participants at the 2024 Haskayne and Fox Accounting Conference, University of Chicago PhD and RP workshops, City University of Hong Kong, HKU Business School, 2024 CAFRAL Annual Conference, 2024 ISB Accounting Research Conference, 2025 HARC, 2025 EFA Annual Meeting, 2025 AAA Annual Meeting, Penn State Smeal College of Business, and Boston College. We are grateful to Jesse Yu-Chieh Kuo for excellent research assistance. This work is supported by the Kilts Center for Marketing, the Kathryn and Grant Swick Faculty Scholarship, and the Ernest R. Wish PhD Fellowship at the University of Chicago Booth School of Business. 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.
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1. Introduction

Americans' trust in institutions has never been lower (Saad, 2023). This is especially true in the banking sector, where the percentage of US adults with high confidence in banks fell from 53% in 2004 to 22% in 2009 following the financial crisis (McCarthy, 2016). This decline was exacerbated by the recent high-profile collapse of Silicon Valley Bank, with an AP-NORC poll showing that only 10% of US adults are left with high confidence in banks while 56% believe that the government does not do enough to regulate financial institutions (Wiseman & Fingerhut, 2023). In this paper, we explore the consequences of declining trust in banks, specifically how trust in banks influences retail borrowers' decisions.[1]

Based on Gambetta et al. (2000) and Sapienza & Zingales (2012), we define trust as "the expectation that another person (or institution) will perform actions that are beneficial, or at least not detrimental, to us regardless of our capacity to monitor those actions." Trust can be compromised through concerns about bankers' motives or banks' operational reliability. A loan agreement is a complex financial contract, and borrowers may be hesitant to enter into such agreements with banks they do not trust. Understanding these contracts often requires specialized financial knowledge that retail borrowers might lack (CFPB, 2024). Retail borrowers have limited resources to conduct due diligence or to take action against a bank that delivers substandard service, leading them to rely on the integrity and competence of bankers to act in their best interest. Thus, trust includes the expectation of fair treatment and the confidence that the bank can competently fulfill its obligations.

While extant literature has explored the determinants of consumers' trust in banks and what changes such trust, much less work has studied how trust influences consumers' financial decisions.[2] The limited research focuses primarily on depositors' behavior and much

[1]Following the literature, we use the terms "trust" and "confidence" interchangeably (Giannetti & Wang, 2016; Sapienza & Zingales, 2012).

[2]See, for example, Fungáčová et al. (2019); Jansen et al. (2015); Van Der Cruijsen et al. (2023) who explore factors that determine consumers' trust in banks and public institutions, and Knell & Stix (2015); Sapienza & Zingales (2012); Stevenson & Wolfers (2011) who study how trust is affected by the global financial crisis.

less on borrowers (Chen et al., 2023; Das et al., 2024; Osili & Paulson, 2014; Van Der Cruijsen et al., 2012; Yang, 2025). However, borrowers are essential to banks' financial health, as the interest margin from intermediating between depositors and borrowers and fees charged on loan products are significant revenue sources for banks. We address the gap in the literature by examining how borrowers respond to an adverse event that lowers their confidence in banks.[3]

An empirical challenge in studying how borrowers respond to declining trust in banks is that measures of trust, which are generally survey-based, tend to be regional or economy-wide rather than bank-specific and thus might be confounded by region-specific factors. We approach this challenge by examining bank-specific events that adversely affect trust. Specifically, we study enforcement actions (also referred to as enforcement decisions and orders, or EDOs) issued by US bank supervisors against financial institutions. When other supervisory measures prove insufficient, bank regulators turn to enforcement actions to compel institutions engaged in unsafe or unsound practices to implement corrective measures (Curry et al., 1999; Eisenbach et al., 2017; Hirtle et al., 2020). Banks subject to EDOs also incur regulatory fines and may have to implement costly operational modifications to comply with EDO stipulations.

Importantly, EDO banks suffer significant reputational damage, as enforcement actions are publicized in the local news media and on regulators' websites. Reputation and trust are distinct but related concepts (Nooteboom, 2002). Reputation is an informational signal based on past behavior that can inform expectations about future behavior (i.e., trust). Thus, enforcement actions can harm banks' reputations by publicly signaling poor governance, which, in turn, can drive consumers' trust-based decisions.

Our approach of using bank enforcement actions to measure changes in trust is consistent with prior research which finds that, apart from severe systemic events like the global

[3] Thakor & Merton (2025) propose a theory of trust in lending. While their study focuses on banks' trust advantage over nonbanks arising from deposit insurance, we exploit the heterogeneity in trust in banks due to supervisory actions.

financial crisis, a range of adverse developments such as negative media coverage, declining stock prices, lack of transparency in product information, and excessive executive compensation are linked to diminished trust in banks (Fungáčová et al., 2019; Jansen et al., 2015; Van Der Cruijsen et al., 2023). Relative to these events, EDOs have the added advantage of being covered in the local news media (Delis et al., 2020; Dyck et al., 2008; Kleymenova & Tomy, 2022). This feature of our setting helps us better identify changes in consumers' trust. The way that local news media reports on bank enforcement can significantly influence public perception and confidence in banks (Dai et al., 2015; Dyck et al., 2008; Miller, 2006; Miller & Skinner, 2015). If the news media discusses enforcement actions negatively, it should lead to a decline in consumers' trust. On the contrary, if the propagated narrative is neutral or positive, then consumers' trust in banks may not be adversely affected. Furthermore, consumers are more likely to learn about EDOs or gain a negative impression of a local bank through local news rather than by accessing regulatory disclosures. Consequently, although EDOs are issued at the bank level, borrowers in different regions may exhibit varying responses to an EDO, influenced by how local media portrays bank enforcement and by disparities in access to regional news. Therefore, we leverage regional variation in news media to further demonstrate how trust in banks impacts borrower decisions.

We expect declining trust in banks to have a greater impact on higher-quality borrowers, as they often have access to alternative sources of credit and maintain multiple banking relationships, giving them greater latitude to avoid transacting with a bank they perceive as untrustworthy. Trust is the expectation that a bank will act in a way that is beneficial for its customers, even when those customers cannot fully monitor its actions (Gambetta et al., 2000; Sapienza & Zingales, 2012). Enforcement actions may undermine this expectation through several channels. First, they are frequently accompanied by fines, sanctions, or management turnover, raising concerns about the bank's reliability. Second, enforcement actions can reveal service quality problems that borrowers may not otherwise observe. Finally, some borrowers may prefer not to transact with banks that have engaged in unethical behavior. These concerns are particularly salient for higher-quality borrowers, who tend to be more attentive to service standards and more responsive to signals of institutional weakness. As a result, they may migrate to more stable banks in anticipation of diminished service or higher loan rates from EDO banks. Therefore, we begin our analyses by investigating whether new borrowers of EDO banks are of worse quality relative to control banks.

We use granular data on auto loans from a credit reporting agency, which links borrowers and lenders. Auto loan pricing can be complex, as rates vary based on the borrower's credit score, loan structure, and vehicle type, forcing them to rely on banks to interpret loan terms. Promotional offers and add-on products can obscure the actual cost of financing and inflate expenses, making it difficult for borrowers to discern the full cost of the loan.[4] Furthermore, supervisors from the Consumer Financial Protection Bureau (CFPB) have found auto loan providers to overcharge for add-on products, wrongfully repossess vehicles, and mislead customers about loan payments (CFPB, 2022). These factors underscore the importance of borrowers' trust in banks in the auto loan market.

Also, auto loans are sufficiently short-term (with mean term of 50 months) and thus allow us to observe most loans from origination to termination within our sample period. We focus only on newly initiated loans so that changes in loan quality are not confounded by EDO-related changes in banks' loss recognition or monitoring practices. Also, the data include the borrower's location, enabling us to exploit geographic variation in trust for the same bank.

We utilize survival models in our main specification as it allows us to simultaneously model both the occurrence and time to delinquency (Gross & Souleles, 2002). Loans originated following the issuance of an enforcement action are of relatively lower quality and become delinquent 28% sooner than those originated by control banks. The results are concentrated in the first year of the enforcement action, suggesting that consumers react to news

[4]See, for example, *CFPB Publishes Research Finding Higher Price Complexity Leads Consumers to Pay More* (`https://www.consumerfinance.gov/about-us/newsroom/cfpb-publishes-research-finding-higher-price-complexity-leads-consumers-to-pay-more/`).

of the EDO. Our results are robust to including time-varying bank and local economic controls, year-month fixed effects to account for systemic time-varying factors that contribute to loan delinquencies, and state stratification to account for time-invariant regional differences. Our results are also robust to entropy matching on the geographic footprint of banks' lending activities, and an OLS specification estimating the probability of delinquency and including county×year-month and bank fixed effects to account for time-varying local shocks and lender-specific factors. Importantly, in all of our estimations, we find that loan quality is not significantly different for EDO versus non-EDO banks prior to receiving the EDO, allaying concerns that declining loan quality might have led to the enforcement action.

We next explore borrower credit characteristics at loan origination. Consistent with our loan delinquency results, borrower quality is worse for EDO banks relative to control banks. During the enforcement period, borrowers of EDO banks have on average 0.8%–0.9% lower credit scores, are 3.5 percentage points more likely to have ever had a loan in collections, have 0.94–1.25 percentage points higher loans ever delinquent, have 10%–11% higher loans past due in the previous 12 months, are 3 percentage points more likely to have ever defaulted, and are 0.9 percentage points more likely to have ever filed for bankruptcy compared to borrowers of non-EDO banks. Overall, these results indicate that banks originate worse loans while an enforcement action is open.

Loss of trust generates spillover effects that extend beyond the institutions responsible for the underlying misconduct. For instance, households exposed to corporate fraud reduce stock holdings of both implicated and uninvolved firms (Giannetti & Wang, 2016). Similar spillovers followed the Madoff Ponzi scheme (Gurun et al., 2018). In the banking sector, trust declines broadly in response to the actions of a few banks (Sapienza & Zingales, 2012; Yang, 2025). Consistent with the literature, we show that greater exposure to banks under enforcement is associated with declining loan and borrower quality at non-EDO banks, but improving quality at nonbank financial institutions. The flight of high-quality borrowers from the banking sector and a corresponding improvement in the nonbank borrower pool are consistent with a decline in trust in banks. It also aligns with the findings in Yang (2025), who shows that trust erosion led households to substitute away from traditional banks and toward FinTech and other nonbank lenders.

We provide several additional analyses consistent with trust influencing borrowers' actions. First, borrowers are 11 percentage points less likely to have repeated interactions with banks under enforcement than with control banks, a sizable decline given a baseline repeat borrowing rate of 30%. This suggests that enforcement actions erode trust and disrupt established lending relationships.

Second, we utilize survey data on trust in banks and bankers from the Chicago Booth/Kellogg School Financial Trust Index (Sapienza & Zingales, 2012). We first validate that a higher county-level exposure to EDO banks is indeed associated with greater declines in trust in banks and bankers. Supporting the trust mechanism, when an EDO is associated with a decline in trust, loans originated during the EDO become delinquent 37% faster. In contrast, when enforcement actions are not tied to a decline in trust, the loan performance of EDO banks show little difference to that of control banks.

Third, we measure the sentiment and emotion conveyed by news articles about enforcement actions in the local media. We hand-collect EDO-related news articles across the US and rely on the NRC Emotion Lexicon to generate measures of positive, negative, and trust sentiments from these articles (Mohammad & Turney, 2010, 2013).[5] Consistent with our expectations, the downward shift in borrower quality following EDO issuance is concentrated in regions where media coverage of bank enforcement is more negative. Specifically, for a one standard deviation increase in negative media sentiment, the loans originated by EDO banks while an EDO is active become delinquent 23% faster compared to those of control banks. In contrast, we find no corresponding decline in borrower quality for EDO banks in regions where media coverage conveys positive or trust-related sentiment.

[5]This database provides a crowd-sourced library of words and phrases associated with sentiment and basic emotions.

Finally, declines in trust are unlikely if consumers are unaware of enforcement actions, such as in counties that lack local news coverage. These counties either lack newspaper publications altogether or have limited newsroom capacity to produce community-relevant content (Abernathy, 2020). If a trust mechanism is at work, EDOs should be less likely to influence trust in news deserts because information about EDOs is less likely to be disseminated. Consistent with this, in news deserts, the quality of loans originated by EDO banks while an EDO is active is no different from that of non-EDO banks. These results are robust to controlling for economic and demographic determinants of news deserts that may also be correlated with loan delinquency. We conduct several sensitivity tests and find robust results.

One might argue that borrowers respond to information dissemination itself, such as additional details conveyed or inferred about the bank's financial or operational situation, rather than to changes in their level of trust. Then, the question becomes why, conditional on becoming aware of additional bank-specific information, consumers choose not to transact with EDO banks. One reason could be that borrowers do not believe EDO banks have the integrity to act in their best interest, especially given that they need to enter into complex financial contracts with the banks. A second reason could be that borrowers believe that an EDO bank might not be able to provide quality services or sustain stable relationships. Our definition of trust encompasses both of these reasons.

We next consider three alternative supply-side explanations. First, banks under enforcement might respond by loosening lending standards and expanding credit, thereby attracting lower-quality borrowers. Given the heightened regulatory scrutiny during an EDO, such a strategy is likely difficult to implement. Further undermining the credit expansion explanation, we observe no change in loan amounts, loan size, or interest rates after controlling for borrower quality, and only a modest reduction in loan length. Second, EDO banks may face funding constraints, resulting in reduced lending overall. However, it is counterintuitive that such constraints would prompt them to cut back specifically on high-quality borrowers.

Third, bank employees could become stressed or distracted during an enforcement action, leading to a deterioration in their screening and monitoring efforts. Our evidence favors the trust mechanism rather than this alternative. Specifically, the spillover effects, results based on survey measures of trust, variation in media sentiment and coverage, and the finding that EDO banks have fewer repeat borrowers are inconsistent with this possibility. Overall, our findings instead suggest a demand-side effect: higher-quality borrowers who have more options choose not to transact with an EDO bank.

Our paper makes several contributions. First, we extend the literature on trust in banks by showing that trust impacts borrowers' decisions. Prior research examines how trust in banks influences borrowers' selection between banks and alternative lenders, including FinTech and online platforms (Yang, 2025; Bertsch et al., 2020). We extend this work by showing that declining trust in banks shifts the borrower composition at banks toward lower-quality borrowers.

Second, we contribute to the literature on bank enforcement actions (Berger et al., 2022; Caiazza et al., 2018; Delis et al., 2019; Deli et al., 2019; Kleymenova & Tomy, 2022). EDOs were publicly disclosed following the 1989 Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) to increase the role of market discipline in bank oversight. By using variation in local information quality, we document a novel channel through which the disclosure of enforcement actions impacts banks. We find that the reputational damage from enforcement actions shifts borrower composition toward lower-quality customers, illustrating how public disclosure can compound the effect of enforcement actions.

Third, we contribute to the growing literature on the role of media in shaping financial behavior by examining how the local news media contextualizes and disseminates information about bank enforcement actions (Dai et al., 2015; Dyck et al., 2008; Miller, 2006; Miller & Skinner, 2015). We find greater effects on consumers' financial decisions for enforcement actions reported on with a more negative media sentiment. Our findings align with recent literature highlighting the importance of local news for economic outcomes (Gao et al., 2020;

Heese et al., 2022; Jiang & Kong, 2024; Kyung & Nam, 2023; Leonelli, 2024; Ma et al., 2025).

Finally, our work is also related to literature exploring how trust in institutions shapes investor behavior and asset allocation decisions, including individuals' stock market participation (Abramova et al., 2024; Giannetti & Wang, 2016; Guiso et al., 2008), future credit outcomes (Brown et al., 2019), and the use of professional money managers and investment advisors (Gennaioli et al., 2015; Gurun et al., 2018; Kostovetsky, 2016). We extend this literature by showing how trust in banks affects the behavior of retail borrowers.

2. Data and sample

2.1. Auto loan data

We source loan-level data from TransUnion, which provides a nationally representative 10% random sample of consumer records from their credit archives. We observe individuals whose credit records appear in the TransUnion database starting in July 2000, adding 10% of subsequent new borrowers and removing those who drop out of the sample due to reasons such as death. We combine information from both loan-month and consumer-month panels. The loan-month panel includes time-varying loan-level information, including loan amount, origination date, closure date, delinquency indicators, and time-series tracking of payment behavior. While we do not directly observe interest rates, we impute them using loan principal, maturity, and scheduled payment amount (Granja & Nagel, 2025). The consumer-month panel traces consumer details over time, such as credit score, date of birth, location, and repayment history. We restrict our sample to 2009–2020 because data prior to 2009 contain fewer variables, including some necessary for our analyses.[6]

[6]Major lenders in the auto loan market include banks and captive finance (manufacturer-affiliated lenders). About 80% of new and 40% of used vehicles are financed. As of 2020, commercial banks accounted for a third of the auto loan market share (31% new and 34% used). The remaining loan volumes were accounted for by captive finance (51% new and 7% used), credit unions (13% new and 25% used), and other independent lenders (Zabritski, 2024). Our sample only includes auto loans made by commercial banks.

2.2. *Bank and enforcement action data*

We obtain commercial banks' financial data from Call Reports collected by the Federal Financial Institutions Examination Council (FFIEC). We source data on enforcement actions from the S&P Global SNL Financial database. Following prior research on bank enforcement (An et al., 2024; Kleymenova & Tomy, 2022), we include only severe enforcement actions issued by federal banking regulators. These include cease and desist (C&D) orders, formal or supervisory agreements, consent orders, and prompt corrective action (PCA) orders. For banks subject to multiple enforcement actions, we retain only the first EDO. Then, we merge our sample of enforcement actions with the TransUnion data, keeping only loans issued by commercial banks.[7] Our final sample consists of 2,860 commercial banks, of which 534 received enforcement actions (which last for an average of 4 years) and 2,326 remain in our control sample.

The enforcement process starts when bank examiners assign low CAMELS ratings of 4 or 5 and recommend regulatory intervention. CAMELS are ratings assigned by bank examiners evaluating six key areas: capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to risk. Deficiencies in these six areas, such as inadequate capital, ineffective board oversight, weak internal controls, and excessive risk-taking, can all trigger regulatory actions. Bank supervisors typically begin the enforcement process with informal measures, such as bank board resolutions or memoranda of understanding, and enforcement actions are usually used as a means of last resort to remediate unsafe or unsound banking practices (Curry et al., 1999; Eisenbach et al., 2017; Hirtle et al., 2020). When EDOs are issued, banks are then typically required to develop a timetable for improvement, which entails substantial operational changes to achieve compliance. Failure to adhere to the remediation plan can lead regulators to escalate enforcement actions by imposing fines,

[7] TransUnion provided us with the list of lenders who report credit data to them. We merged these with our sample of enforcement actions and bank financial data. Then, TransUnion matched these observations to the lender key used in their loan panel, removing the bank names to ensure confidentiality.

restrictions on growth, or limits on shareholder payouts. If a bank satisfies the requirements of the EDO, the bank supervisor issues a termination order and bank examiners assign an improved CAMELS rating to the bank. If a bank fails to comply, regulators can enforce the order in court or terminate the bank's deposit insurance.[8]

2.3. Descriptive statistics

Descriptive statistics for our main sample are presented in Table 1 Panel A. All continuous variables are winsorized at the 1st and 99th percentiles of their respective distributions within each sample year. We provide detailed definitions of all variables in Appendix A. The average loan has an imputed annual percentage rate (APR) of 6.4%, amount of $14,559, and term length of 50 months.[9,10] Among the 8.7% of loans that become delinquent, the average time to delinquency is 20 months, with a slightly right-skewed distribution. At loan origination, the average borrower is 42 years old and has a credit score of 680. In addition, 19.2% of borrowers have ever had a loan in collections, 26.0% have ever defaulted on a loan, and 3.4% have ever experienced a bankruptcy.

About 7.6% of loans are issued by EDO banks. Figure 1 shows the geographic distribution of loans made by EDO and non-EDO banks. These loans are scattered across the country and do not appear clustered in any particular area. Regarding bank characteristics, TransUnion permits only the use of decile values for bank-specific variables to preserve bank anonymity. Therefore, we utilize deciles, calculated from the distribution of all commercial banks per year, as bank-level control variables. We lag these variables by one year to reflect the knowledge that borrowers have about the bank at the time of loan origination. Table 1 Panel B compares the characteristics of the EDO and non-EDO banks. EDO banks have a lower return on assets, higher non-performing assets, and a lower capital ratio. These

[8] For a more detailed description of the EDO issuing process, please see Section 2 in Kleymenova & Tomy (2022).

[9] The periodic interest rate is imputed using the initial loan amount, the number of periods, and the payment per period. The APR is then calculated as the number of periods multiplied by the periodic interest rate.

[10] Please note that continuous variables are reported in natural logarithms in Table 1.

weaker performance metrics are expected, as enforcement actions tend to be issued against banks with deficient performance. In later tests, we employ entropy balancing to alleviate concerns about the comparability between EDO banks and control banks, which is discussed in Section 3.1.

3. Baseline results: Loan and borrower quality

Enforcement actions are publicized through the news media and on regulators' websites, and represent significant adverse events for banks. Prior research has found that adverse banking events influence individuals' confidence in banks. For example, several studies find that confidence in the banking sector declined following the 2008 financial crisis (Fungáčová et al., 2019; Knell & Stix, 2015; Sapienza & Zingales, 2012; Van Der Cruijsen et al., 2023). Similarly, Jansen et al. (2015) find that adverse media reports, falling stock prices, opaque product information, and excessive executive compensation are associated with lowered trust in banks. Building on this, we hypothesize that enforcement actions undermine individuals' trust in banks, reducing their likelihood of using banks' services.[11]

Although several studies explore the factors that drive trust in banks, few studies explore whether a loss of confidence in banks influences consumers' financial decisions. Those that do primarily focus on depositor behavior rather than that of borrowers. For example, Osili & Paulson (2014) find that immigrants who experienced a banking crisis in their home country are less likely to have checking accounts with US banks relative to others who emigrated from the same country but did not live through a banking crisis. Specifically exploring bank enforcement, Das et al. (2024) find that news of supervisory penalties on some banks in India leads depositors to withdraw funds from both the penalized and neighboring nonpenalized banks' branches. Consistent with trust in banks influencing depositor behavior, they

[11] Research distinguishes between broad-scope trust (trust in institutions in general) and narrow-scope trust (trust in a specific institution, e.g., in one's own bank). Our approach of using enforcement actions focuses on narrow-scope trust. However, Van Der Cruijsen et al. (2023) find that broad-scope and narrow-scope trust are highly correlated (correlation coefficient of 0.72).

find that withdrawals are more pronounced in regions with lower trust in public institutions (i.e., courts and banks) relative to regions with higher trust. Also, the 2021 FDIC National Survey of Unbanked and Underbanked Households reveals that 33% of unbanked households cite a lack of trust in banks as a reason for not having a bank account (FDIC, 2021).

We extend this literature to examine how a loss of trust in banks could affect borrowers' behavior. Loan agreements are complex financial contracts containing specialized financial terms that borrowers might not understand. Thus, they need to depend on the integrity of bankers to act in their best interest. Unlike corporate borrowers, retail borrowers do not have the bargaining power or resources to conduct extensive due diligence before entering into contracts with banks or pursue recourse in cases of misconduct. Thus, trust is crucial to their ex-ante decisions in selecting a bank, making them less likely to transact with a bank that is poorly managed or engages in misconduct. Such selectivity can only be afforded by those borrowers who have other options, for example, who can more easily access alternative sources of credit or have multiple banking relationships. Thus, higher-quality borrowers, who have more options, should be less likely to transact with a bank that is not trustworthy. Higher-quality borrowers are also more likely to be sensitive to poor service quality and are thus less likely to transact with an EDO bank.

3.1. Delinquency of loans originated during an enforcement action

To assess changes in borrower behavior, we study how the credit quality of originated loans varies over the stages of an enforcement action. Specifically, we follow prior literature to estimate survival models of loan delinquency (Gross & Souleles, 2002; Shumway, 2001). Estimating survival models allows us to consider both the occurrence of and time to delinquency. We estimate the following lognormal accelerated failure time (AFT) model using the loan-month panel data:

$$\begin{aligned}\log(\mathit{Time\ to\ Delinquency})_{itbcs} = {} & \beta_0 + \beta_1 EDO_b + \beta_2 EDO\ Cohort_{tb} \\ & + \beta_3 Bank_{(t-1)b} + \beta_4 Econ_{(t-1)c} + \delta_t + \gamma_s + \varepsilon_{itbcs}\ .\end{aligned} \tag{1}$$

The model predicts how covariates accelerate or decelerate the time to delinquency for a loan. In Equation 1, i indexes the loan, t the year-month of loan origination, b the bank, c the local geographic region (census tract), and s the state. The dependent variable, *Time to Delinquency*, is the survival time and represents the number of months a loan remains current before it goes delinquent.[12] *EDO* is an indicator for loans originated by banks that receive enforcement actions. *EDO Cohort* represents indicators for the following groups: *Pre EDO*$_{[\tau-3,\tau-1]}$, *During EDO*$_{[\tau]}$, and *Post EDO*$_{[\tau+1,\tau+5]}$, where τ represents all years that an EDO is active. *Pre EDO* is an indicator for loans issued one to three years before a bank receives an enforcement action, *During EDO* is an indicator for loans issued while an enforcement action is active, and *Post EDO* is an indicator for loans issued one to five years after the termination of the enforcement action. The variables *Bank* and *Econ* are lagged controls for bank characteristics and local economic conditions, respectively, which are expected to influence the likelihood of and time to delinquency. *Bank* includes yearly deciles of bank size, profitability, liquidity, capital ratio, and nonperforming assets. *Econ* includes census-tract-level unemployment rate and yearly percent growth in per capita income.[13] We include year-month fixed effects (δ_t) to account for time-varying factors that contribute to loan delinquencies and stratify by state (γ_s) to account for time-invariant regional differences. Finally, ε is the error term.

Our sample includes loans originated by all banks. We include the full sample of loans

[12] Loans are considered delinquent in the first month of nonrepayment and drop out of the sample thereafter (Gross & Souleles, 2002). For loans that are marked delinquent after the termination date, we consider them delinquent in the last period before termination if they are marked delinquent within six months after termination. This is a reasonable assumption, as there is often a delay between the loan delinquency and the bank reporting it to the credit agency, and the majority of these delayed delinquencies in our sample are documented within six months of termination. Delinquencies showing longer delays could be due to other unrelated errors, so we exclude those from the sample. Observations are at the loan-month level, and the survival model uses the delinquency indicator to implicitly calculate loan-level *Time to Delinquency*.

[13] Our data on population demographics is sourced from the US Census Bureau's American Community Survey (ACS). Since ACS 1-year data is only available for areas with populations of 65,000 or more, we use ACS 5-year estimates, which are available for all census tracts. ACS 5-year data is also more representative of regional demographics over time as it averages annually collected data over the current and preceding four years. Except for observations in 2009 (when ACS 5-year data begins), we lag these variables by one year.

because the survival model implicitly assumes that all loans have some non-zero probability of delinquency and thus contribute some information, increasing the accuracy of our estimates (Singer & Willett, 2003). For EDO banks, we drop observations following *Post EDO*$_{[\tau+1,\tau+5]}$ and treat the years before the *Pre EDO* period as the baseline. If a loss of consumers' trust causes EDO banks to lose high-quality borrowers, we expect loans originated in the *During EDO* period to be of lower quality, that is to go delinquent sooner, relative to non-EDO banks and the baseline. Then, if trust in the bank recovers after EDO termination, loans originated in the *Post EDO* period should go delinquent slower than *During EDO* loans. Finally, we are agnostic about the sign of the *Pre EDO* coefficient. On the one hand, the coefficient could be negative if the bank had declining borrower health caused by risky lending before the EDO, which could be the reason for enforcement. However, if the bank received an EDO for reasons unrelated to borrower quality, the coefficient could be close to zero. Thus, including *Pre EDO* helps us evaluate the potential concern that risky lending was the cause of the enforcement action rather than vice versa.

In Figure 2, we plot the hazard function, which shows how the instantaneous risk of delinquency changes over time for loans originated in each *EDO Cohort*. The risk of delinquency increases from loan inception, reaches its maximum around 20 months after inception, and declines thereafter. Importantly, throughout the life of the loan, the probability of delinquency is highest for loans originated when an EDO is in effect (that is, in the *During EDO* period). The next highest probability of delinquency is for the cohort of loans originated in the five years following EDO termination (the *Post EDO* period), consistent with banks gradually recovering from the impact of enforcement. This diminishing impact of EDOs on trust in banks aligns with the findings in Yang (2025) and Gurun et al. (2018) that the trust effects of exposure to scandals tend to fade relatively quickly. Moreover, because EDOs draw increased supervisory attention, their successful termination can signal institutional improvements within the bank (An et al., 2024). We also observe that the probability of delinquency is similar for loans originated in the three years before an EDO (the *Pre*

EDO period) and the control sample of loans originated by non-EDO banks, indicating that declining borrower health is unlikely to be a primary driver of EDO issuance.

In Table 2, we tabulate the results from estimating Equation 1. Consistent with our prediction, column (1) shows that loans originated during EDOs are of lower quality relative to the control. The statistically significant *During EDO* coefficient of -0.324 indicates that loans originated while an EDO is active become delinquent 28% sooner than those originated by control banks.[14] In column (2) of Table 2, we use entropy balancing to mitigate the concern that EDO banks may systematically differ from non-EDO banks in their lending footprint, resulting in differences in long-term loan outcomes.[15] Specifically, we match EDO and non-EDO banks on the first two moments of the number of auto loans originated at the bank-state level, and we re-balance our sample for every year.[16] Using the entropy-balanced sample, column (2) shows a statistically significant *During EDO* coefficient of -0.309, suggesting that loans originated by EDO banks while an EDO is active become delinquent 27% sooner than those originated by control banks. In column (3) we partition the *During EDO* indicator into *During EDO 1*, an indicator for the first year following EDO issuance, and *During EDO 1+*, an indicator for all subsequent years an EDO is active. Borrowers' response to a decline in trust is likely to be more pronounced immediately after EDO issuance, when news outlets typically cover enforcement actions. Consistent with this, we find the decline in the quality of new loans is concentrated in the first year of EDO issuance while the coefficient becomes insignificant and slightly attenuated in magnitude in subsequent years. Across all three columns, we do not see a significant coefficient on *EDO*

[14] These magnitudes are calculated as $(1 - e^{-0.324}) \times 100$. This is illustrative of the calculation we conduct in all subsequent analogous cases.

[15] Entropy balancing utilizes an optimization algorithm to construct weights for treated and control units under a set of balancing constraints (Hainmueller, 2012). Unlike most other matching methods, entropy balancing does not simply discard unmatched observations, thus preventing the loss of information arising from a reduction in sample size.

[16] We utilize the entropy-balanced sample in all subsequent analyses unless otherwise noted. In our main analysis, we match EDO and non-EDO banks on the first two moments of the number of auto loans granted at the bank-state level. In additional robustness checks, we balance the sample based on the first two moments of the amount of auto loans granted at the bank-state level and find consistent results.

or *Pre EDO*, suggesting that, conditional on bank characteristics, neither the level nor the pre-period change in borrower quality triggered the enforcement action.

Using a survival model enables us to incorporate both the occurrence of and time to delinquency in our estimation, but it statistically limits the granularity of fixed effects we can include. To address this limitation, we re-estimate Equation 1 using an OLS model with the dependent variable *Delinquency*, which is an indicator for whether a loan goes delinquent at any point during its life. This allows us to include granular county × year-month fixed effects, further removing unobservable time-varying factors unique to each county. We also augment time-varying bank-level controls with bank fixed effects that capture unobservable time-invariant characteristics unique to each bank. With these more stringent fixed effects, we find consistent results: loans originated by EDO banks in the *During EDO* period are 2.4 percentage points more likely to become delinquent relative to those originated by control banks (see Table IA1 of the Internet Appendix). Also consistent with the survival model results, the coefficients on *Pre EDO* and *Post EDO* are not statistically significant.

3.2. Quality of new borrowers during an enforcement action

Given that we observe increased loan delinquencies, we next ask whether borrowers of EDO banks are of observably worse quality at the time of loan issuance. Specifically, we estimate the following OLS model:

$$\begin{aligned} \mathit{Borrower\ Characteristic}_{i(t-1)bc} = \beta_0 + \beta_1 \mathit{EDO}_b + \beta_2 \mathit{EDO\ Cohort}_{tb} + \gamma_1 \mathit{Borrower\ Age}_{it} \\ + \gamma_2 \mathit{Econ}_{(t-1)c} + \eta_c + \alpha_b + \delta_t + \varepsilon_{itbc}\ . \end{aligned} \tag{2}$$

The dependent variable, *Borrower Characteristic*, represents various credit and financial history variables for a borrower as of the month before loan origination. These include the borrower's credit score (*Credit Score*), whether the borrower ever had a loan in collections (*Collections*), the percentage of loans that have ever been delinquent for the borrower (*% Delinquent*), the total past-due loan amount in the last 12 months for the borrower (*Past Due (12mo)*), whether the borrower has ever defaulted on a loan (*Defaults*), and whether the borrower has ever filed for bankruptcy (*Bankruptcy*).The variable *Borrower Age* represents the natural log of the borrower's age at the time of loan origination, which we control for because it likely impacts the length of credit history available, credit utilization rates, and experience in managing credit effectively, all of which could impact financial health. The variable *Econ* represents lagged local macroeconomic variables (per capita income growth and unemployment rate) that account for changes in census-tract-level economic conditions that might influence borrowers' credit characteristics. η_c, α_b, and δ_t represent county, bank, and year-month fixed effects, respectively, and we also include county $\times$ year-month fixed effects in alternative specification.

In Table 3, we present results from the estimation of Equation 2. Columns (1) and (2) show that the borrowers of loans originated in the *During EDO* period have worse credit scores compared to those originated by control banks. On average, borrower credit scores are 0.8%–0.9% lower in the *During EDO* period, which translates into a score difference of 6 points.[17] Around an already high average, this is a modest but economically significant decline. Consistent with the results for credit score, columns (3)–(8) show that borrowers of EDO banks in the *During EDO* period are 3.5 percentage points more likely to have ever had a loan in collections, have 0.94–1.25 percentage points higher loans ever delinquent, and have 10%–11% higher loans past due in the last 12 months. Furthermore, columns (9) and (11) indicate that borrowers of EDO banks are 3 percentage points more likely to have ever defaulted and 0.9 percentage points more likely to have ever filed for bankruptcy. Overall, the results in Table 3 are consistent with those in Table 2, indicating that borrowers of loans originated by EDO banks while the EDO is open are of worse quality compared to borrowers of loans originated by control banks.

[17] We calculate this as the pre-EDO average score of 689 multiplied by 0.8%, which yields a difference of 5.51 points.

4. Exploring the mechanism: Trust in banks

In this section, we present analyses to substantiate the trust mechanism, specifically documenting shifts in trust and its impact on retail borrowers. First, we examine whether declining trust spills over to the broader banking sector. Under a trust-based mechanism, borrowers should withdraw not only from EDO banks but also from non-EDO banks depending on their exposure, and shift their activity toward nonbanks. Second, we examine whether banks under enforcement experience a decline in repeat borrowers, a natural consequence of deteriorating trust. Third, we incorporate survey-based measures of trust in banks and bankers to directly test whether trust erosion translates into larger declines in borrower quality, as high-quality borrowers become more likely to exit. Fourth, we analyze how the local media covers bank enforcement actions, measuring the sentiment and emotional tone of news coverage to assess whether more negative media narratives amplify trust effects. Finally, we exploit variation in local information environments to test whether the impact on borrower composition depends on consumer awareness. If trust degradation drives our results, enforcement actions should have weaker effects in areas where borrowers are less informed about regulatory interventions.

4.1. Spillovers to nonbank financial institutions

Several studies show that declining trust can generate broad spillover effects that extend well beyond the institutions responsible for the underlying misconduct. For instance, Giannetti & Wang (2016) shows that exposure to corporate fraud in a state leads households to reduce their holdings of both fraudulent and non-fraudulent firms' stocks. Gurun et al. (2018) documents similar effects following the Madoff Ponzi scheme, and both Yang (2025) and Sapienza & Zingales (2012) find that misconduct by a few institutions can trigger broad declines in trust across the banking sector. When trust is banks erodes, borrowers might interpret adverse actions of even a few banks as evidence of sector-wide unreliability. As a result, borrowers may withdraw from banks altogether and instead reallocate their activity to other financial institutions outside the distrusted category, such as nonbank financial institutions.

To evaluate whether borrowers withdraw from the banking sector and reallocate toward nonbanks, we estimate the following AFT model:

$$\begin{aligned}\log(\textit{Time to Delinquency})_{itbcs} &= \beta_0 + \beta_1 \textit{Exposure to EDO}_{tc} \\ &\quad + \beta_3 \textit{Bank}_{(t-1)b} + \beta_4 \textit{Econ}_{(t-1)c} + \delta_t + \gamma_s + \varepsilon_{itbcs} \ .\end{aligned} \tag{3}$$

Exposure to EDO is the county-year share of loans issued by EDO banks while the enforcement action is active, defined as a proportion between 0 and 1. All other variables are as defined before. Results from the estimation of Equation 3 separately for non-EDO banks and nonbank financial institutions are presented in Table 4 Panel A. Column (1) suggests that non-EDO banks in counties with greater exposure to EDO banks experience a decrease in time to delinquency relative to those in less-exposed counties, although the coefficient is not statistically significant at conventional levels. Column (2), however, shows that exposure to EDOs significantly increases time to delinquency for nonbank financial institutions, consistent with high-quality borrowers shifting toward nonbanks.

We also evaluate the quality of new borrowers at non-EDO banks and nonbank financial institutions based on their exposure to EDO banks. Specifically, we estimate the following OLS model:

$$\begin{aligned}\textit{Borrower Characteristic}_{i(t-1)bc} &= \beta_0 + \beta_1 \textit{Exposure to EDO} + \gamma_1 \textit{Borrower Age}_{it} \\ &\quad + \gamma_2 \textit{Econ}_{(t-1)c} + \eta_c + \alpha_b + \delta_t + \varepsilon_{itbc} \ .\end{aligned} \tag{4}$$

All variables are as defined before. Table 4 Panel B presents the results from the estimation of Equation 4 for non-EDO banks, whereas Table 4 Panel C presents the results for nonbank financial institutions. These results corroborate our findings in Panel A that higher exposure to EDO banks is associated with lower-quality borrowers at non-EDO banks and higher-quality borrowers at nonbank financial institutions.

Overall, our results in Table 4 show that exposure to EDO banks generates spillovers consistent with a trust-driven exodus from the banking sector. Improvements in borrower quality at nonbanks and declines in quality at non-EDO banks strongly suggest a mechanism beyond bank-specific reputation. A reputation channel would imply a penalty only for the offending banks. Instead, we observe a sector-wide penalty, consistent with borrowers withdrawing trust from the banking sector, depending on their exposure to the EDO banks. This interpretation aligns with the findings in Yang (2025), who shows that trust erosion leads borrowers to substitute away from traditional banks toward FinTech and other nonbank lenders. Next, we present additional evidence consistent with the trust mechanism.

4.2. Repeat borrowers

If declining trust drives borrowers away from sanctioned banks, we should observe fewer repeat borrowers at EDO banks relative to control banks. To test this prediction, we reestimate Equation 2, replacing the dependent variable with *Repeat*, an indicator equal to one if the loan represents a repeated relationship rather than the borrower's first loan with the bank. Table 5 presents the results. We find that repeat borrowers are 11 percentage points less likely at banks under enforcement compared to control banks, a substantial magnitude relative to the baseline repeat borrower rate of 30%. The table also shows that repeat borrowers are 13%–14% percentage points less likely in the *Post EDO* period, indicating that these borrowers do not return after the EDO is terminated. In relation to our findings in Table 2 and Table IA1, these results suggest that the improvement in delinquency after EDO termination is driven by new borrowers. These findings are consistent with trust erosion leading to a disruption of bank-customer relationships.

4.3. Survey evidence on trust in banks and bankers

Next, we provide evidence for a trust mechanism driving our results using survey data on trust in banks and bankers. We expect our results to be stronger in cases where an EDO is associated with greater declines in trust. We utilize the Chicago Booth/Kellogg School Financial Trust Index data available from 2009 to 2021 (Sapienza & Zingales, 2012). The index was constructed by annually surveying over 1,000 randomly selected American households about their trust in various financial institutions.[18] Survey participants were asked the following question:

> *On a scale from 1 to 5 where one means "I do not trust them at all" and five means "I trust them completely," can you please tell me how much do you trust... [Banks, Bankers, Brokers, Mutual funds, Stock market, Insurance companies, The Government, Large corporations, The market system, The Federal Reserve Bank, Other people in general]?*

Based on the survey responses, we create two measures (*Trust (Banks)* and *Trust (Bankers)*) which are indicators for an average response of 4 or higher for trust in banks and bankers, respectively, in each county-year.

We begin by validating that EDOs are indeed associated with declines in these survey-based measures of trust. Specifically, we assess whether higher county-level exposure to EDO banks is associated with greater declines in trust in banks and bankers. We define *High Exposure to EDO* as an indicator for the top tercile of the proportion of total loan volume within a county issued by banks under active EDOs. We estimate an OLS model regressing *Trust (Banks)* and *Trust (Bankers)* on *High Exposure to EDO* in addition to year and state fixed effects. The results, presented in Table 6 Panel A, indicate that high exposure to EDO banks is associated with a 5.7–5.8 (5.6–5.7) percentage-point lower level of trust in banks and bankers.[19]

Next, we turn to our main specification and examine whether borrower quality declines more at EDO banks when EDOs lead to greater declines in trust, as indicated by the survey-based measures. Specifically, we estimate variations of the following lognormal AFT model:

[18] Gallup and other leading polling organizations also use samples of 1,000-1,500 respondents because this range provides an optimal balance between statistical accuracy and cost (Newport et al., 1997).

[19] In an untabulated robustness test, we also measure exposure to EDO banks using county-level deposits and find similar results.

$$
\begin{aligned}
\log(\textit{Time to Delinquency})_{itbcs} = {} & \beta_0 + \beta_1 EDO_b + \beta_2 EDO\ Cohort_{tb} + \beta_3 Decline\ in\ Trust_{ct} \\
& + \beta_4 EDO_b \times Decline\ in\ Trust_{ct} \\
& + \beta_5 EDO\ Cohort_{tb} \times Decline\ in\ Trust_{ct} \\
& + \gamma_1 Bank_{(t-1)b} + \gamma_2 Econ'_{(t-1)c} + \delta_t + \gamma_s + \varepsilon_{itbcs}\ ,
\end{aligned} \tag{5}
$$

where *Decline in Trust* is either an indicator or a continuous variable that captures the decline in trust (explained below). *Econ′* comprises a range of local economic and demographic variables at the census tract level, including per-capita income growth, unemployment rate, population size, level of per-capita income, average age of the population, and level of urbanization. The remaining variables are as described earlier.

Our measures of trust are calculated as the bank-level loan-weighted average of trust in banks across all counties where a bank makes loans. To construct the indicator *Decline in Trust (Dummy)* for each EDO, we compare trust in the years before and after EDO issuance, defining the indicator as one when trust decreases post-EDO and zero otherwise. Approximately 70% of EDOs are associated with such declines. To construct the continuous measure *Decline in Trust (Percentage)*, we subtract trust after EDO issuance from trust before EDO issuance in counties affected by EDOs.

Results from the estimation of Equation 5 are presented in columns (1) and (2) of Table 6 Panel B. Column (1) uses *Decline in Trust (Dummy)* as the interaction variable and shows a stronger change in time to delinquency when EDOs are associated with a decline in trust. When an EDO is not associated with a decline in trust, loans originated during EDOs are no different than loans originated by control banks. However, when EDOs are associated with a decline in trust, loans originated during EDOs become delinquent 37% faster than when there is no decline in trust, as indicated by the *During EDO* $\times$ *Decline in Trust* coefficient of -0.456. Column (2) uses *Decline in Trust (Percentage)* as the interaction variable and yields consistent inferences.

Columns (1) and (2) look at a simultaneous change in trust in banks and borrower behavior. In Column (3), we utilize an *ex ante* measure of trust from Hayes et al. (2021). This state-level measure is a weighted average of origin-country trust levels (from the World Value Survey and European Value Survey), with weights based on each ancestral ethnic group's share of the local population. The decline in borrower quality is driven primarily by states with below-median *ex ante* trust. These results also support a trust-based mechanism behind reduced loan quality at EDO banks.

4.4. Sentiment and emotion in the local news coverage of bank enforcement

Next, we consider how the local news media discusses bank enforcement actions. Local media outlets can affect consumers' trust in banks by creating and disseminating news about banks (Dai et al., 2015; Dyck et al., 2008; Miller, 2006; Miller & Skinner, 2015). While the baseline news content is often created by other parties (i.e., regulators who issue enforcement actions), news outlets play an active role in disseminating this information in an accessible format to the general public. They also influence public opinion by contextualizing news, for instance by highlighting the importance of a bank to the local economy or discussing the implications of bank violations (see Appendix B for examples of media coverage of bank enforcement). Furthermore, research suggests that local news plays an important role in creating awareness of local events and increasing community interaction (Mathews, 2022), potentially amplifying collective negative sentiment towards offending banks. Thus, given the trust channel we propose, declines in trust should be more severe in areas where the tone in media reports discussing bank enforcement is more negative.

To examine the tone of local news articles, we hand-collect news articles related to EDOs from the NewsBank database. Given our focus on the local information environment, we limit our sample to articles from local news sources, excluding online-only and national media.[20] To measure the sentiment and emotional content of these news articles, we utilize

[20] We focus on local news because our data identifies borrower locations but not bank locations, which are anonymized by TransUnion. Figure IA1 of the Internet Appendix shows the geographic distribution of EDO-related articles.

the NRC Emotion Lexicon, which provides a crowd-sourced library of words and phrases associated with sentiment and basic emotions (Mohammad & Turney, 2010, 2013). We break down the article text into individual words and match each word against the Lexicon.[21] We count the number of matching words for each relevant sentiment or emotion, allowing each word to be associated with multiple sentiments. The raw count of each sentiment is then scaled by the number of words in the article to arrive at a normalized score for each sentiment in each article. Our final measure *Sentiment* is the state-year mean of these scores for each sentiment.[22] The news articles are matched to loans based on borrower location, allowing our measure to reflect the overall tone of local media coverage related to bank enforcement in a particular location.

To assess how the sentiment and emotional content of news articles impacts borrowers' response to EDOs, we estimate the following lognormal AFT model:

$$\begin{aligned}\log(\textit{Time to Delinquency})_{itbcs} = \beta_0 &+ \beta_1 EDO_b + \beta_2 EDO\ Cohort_{tb} + \beta_3 Sentiment_{ts} \\ &+ \beta_4 EDO_b \times Sentiment_{ts} + \beta_5 EDO\ Cohort_{tb} \times Sentiment_{ts} \\ &+ \gamma_1 Bank_{(t-1)b} + \gamma_2 Econ_{(t-1)c} + \delta_t + \gamma_s + \varepsilon_{itbcs}\ .\end{aligned} \tag{6}$$

Sentiment is the continuous variable described above. The remaining variables are described before. We focus on negative, positive, and trust sentiments. We expect that our findings of decreased loan quality during EDOs are concentrated in regions where the local news media coverage of bank enforcement is overwhelmingly negative. We do not expect our findings to hold in regions where sentiment is positive or associated with trust.

Table 7 presents results from the estimation of Equation 6. Column (1) presents results where *Sentiment* represents negative sentiment. In columns (2) and (3), *Sentiment* represents positive sentiment and trust, respectively. In line with our expectations, we only

[21]In Figure IA2 of the Internet Appendix, we present the top 30 words from our sample that are most strongly associated with each sentiment.

[22]Given the sparsity of enforcement actions, we aggregate our measures to the state-year level. In state-years with missing data, we impute missing sentiment and emotion measures by carrying forward the most recently available values.

see a decline in borrower quality in states where the local media discusses bank enforcement in a negative way. Specifically, column (1) shows that, when an EDO is not associated with negative media sentiment (*Sentiment = 0*), loans originated by EDO banks when an EDO is active are no different than loans originated by control banks. However, for a one standard deviation increase in negative sentiment, loans originated during an EDO become delinquent 23% faster compared to those originated by control banks, as indicated by the *During EDO* $\times$ *Sentiment* coefficient of -5.579.[23] Columns (2) and (3) show that positive sentiment and trust is not associated with decline in loan quality for EDO banks. Overall, these results underscore the importance of borrowers' trust in banks as a mediating mechanism.

4.5. Quality of the local information environment

Finally, we leverage regional variation in access to local news. In areas with limited news dissemination, consumers are less likely to be exposed to information about bank enforcement and, consequently, less likely to lose confidence in EDO banks. News deserts, defined by Abernathy (2020) as "a community, either rural or urban, where residents have very limited access to the sort of credible and comprehensive news and information that feed democracy at the grassroots level," are a suitable proxy for poor local information for two reasons. First, news deserts are an unambiguous indicator for poor information environments because they are counties where either there are no local newspapers in circulation or the existing local newspapers have such diminished newsrooms that they are unable to publish community-relevant information (Abernathy, 2020). Even though people might obtain news digitally, most online sources of local news are also operated by local newspapers while nationally available news does not typically cover local events such as EDOs issued to small local banks. Thus, obtaining local information in a news desert requires significantly more effort (Mathews & Ali, 2023). Second, research finds that a lack of local news dilutes bonds between community members because newspapers often act as a central source

[23] The economic magnitude is calculated as $(1 - e^{-5.579 \times 0.046}) \times 100$.

of shared information, fostering a sense of community identity and engagement (Mathews, 2022). Without newspapers, residents lose a common platform for local news and events, leading to reduced communal interaction and local awareness. Therefore, word-of-mouth transmission of financial information, such as a poor experience with a bank, is also less likely to transmit between individuals in news deserts.

Thus, enforcement actions are less likely to lead to declines in trust in news deserts, as borrowers are less likely to be informed about these actions. To test this, we first repeat the specification from Table 6 Panel A but include an interaction term for news deserts. In Table 8 Panel A, we show that exposure to EDOs does not lower trust in banks or bankers in news deserts, where a lack of local media coverage prevents consumers from learning about EDOs and thus limits reputational costs.

Next, we estimate the following AFT model to explore heterogeneity in our baseline:

$$\begin{aligned}\log(\mathit{Time\ to\ Delinquency})_{itbcs} = \beta_0 &+ \beta_1 EDO_b + \beta_2 EDO\ Cohort_{tb} + \beta_3 News\ Desert_c \\ &+ \beta_4 EDO \times News\ Desert_c + \beta_5 EDO\ Cohort_{tb} \times News\ Desert_c \\ &+ \gamma_1 Bank_{(t-1)b} + \gamma_2 Econ'_{(t-1)c} + \delta_t + \gamma_s + \varepsilon_{itbcs}\ .\end{aligned} \tag{7}$$

News Desert is an indicator for a county defined as a news desert by Abernathy (2020) (see Figure 3 for a distribution of news deserts across counties).[24] We also control for several local economic and demographic variables at the census tract level that could be correlated with news deserts. For instance, economically disadvantaged or rural counties are more likely to be news deserts, as they may be unable to sustain a local newspaper through subscriptions and advertising revenue. Therefore, we include per-capita income growth and

[24]Our data on news deserts is sourced from the UNC Hussman School of Journalism and Media's Center for Innovation and Sustainability in Local Media. The database identifies local newspapers that conduct journalism serving the public interest. Importantly, it excludes shoppers, newsletters, specialized publications, promotional inserts, and certain zoned editions that do not represent public interest journalism. The data is collected in rounds, which occur in 2004, 2014, 2016, 2018, and 2020. Given that our sample spans 2009 to 2020, we take an *ex ante* time-invariant definition of news deserts from the 2004 data. The data collection staff also indicated that data from the 2014 and 2016 collection rounds are less accurate.

level, unemployment rate, and the degree of urbanization as economic controls. News deserts also tend to have declining and older populations (Abernathy, 2020), so we control for the size and average age of the population. In the most stringent specification, we also interact *News Desert* with each of these control variables to address the concern that economic and demographic conditions differentially impact loan quality in news deserts relative to other areas. The remaining variables are as defined before.

Results from the estimation of Equation 7 are presented in Table 8 Panel B. Column (1) includes bank-level controls and economic controls of per-capita income growth and unemployment rate. Column (2) adds additional economic controls that could be associated with the occurrence of news deserts. Column (3) further interacts *News Desert* with each of the economic controls. Consistent with our expectations, Table 8 shows that loans originated in news deserts during an EDO are not of lower quality. Column (1) indicates that, when a borrower does not reside in a news desert, loans originated during an EDO become delinquent 27% faster compared to those originated by control banks, as indicated by the *During EDO* coefficient of -0.320. This aligns closely with our earlier findings in Table 2. However, for borrowers in news deserts, the time to delinquency for loans originated during an EDO is not significantly different from that of loans originated by control banks, evidenced by an insignificant z-statistic for the sum of the *During EDO* and *During EDO* $\times$ *News Desert* coefficients (z-statistic $= 1.316$). We find qualitatively similar results in Columns (2) and (3).

Given the negative and significant *News Desert* coefficient in Column (3) of Table 8, one potential concern is that banks receiving EDOs operate in economically distressed areas, which are systematically more likely to be news deserts. However, because the coefficients on *EDO* $\times$ *News Desert* and *Pre EDO* $\times$ *News Desert* are insignificant, this is unlikely to be systematically correlated with EDO timing, reducing the concern for our identification strategy. Moreover, even if the timing did align, the *During EDO* $\times$ *News Desert* coefficient should be negative because borrower quality should be relatively worse in news deserts during an EDO, which is also inconsistent with our findings.

We also conduct further robustness tests to ensure that we indeed capture the quality of local information rather than underlying economic or demographic factors. First, we show that financial distress does not drive our findings by reestimating Equation 7 including *Low Income*, an indicator for lowest-tercile individual or household median income in a census tract, and its interactions with *EDO Cohort* (see Table IA2 of the Internet Appendix). Second, we match non-news desert counties with news desert counties on several economic and demographic variables and reestimate Equation 7 using this matched sample (see Table IA3 of the Internet Appendix).[25] Third, we replace *News Desert* with two alternative measures of low-quality local information used in the literature: local newspaper closures and count of newspaper establishments (see Table IA4 and Table IA5 of the Internet Appendix).[26,27] We find consistent results in all three robustness tests. Overall, the findings in this section support a trust-based mechanism explaining the deterioration in loan quality during EDOs.

5. Additional analyses

5.1. Supply-side changes

We conduct additional tests to alleviate the concern that supply-side changes fully explain our results. Specifically, if EDOs put banks under increased financial pressure, this could induce them to expand their total supply of credit, which would almost necessarily involve lending to lower-quality borrowers. Moreover, to obtain more borrowers, EDO banks

[25] These variables include per-capita income level and growth, unemployment rate, population size, average age of the population, and level of urbanization. We perform propensity score matching with replacement. We have 178 news-desert counties and we pair with 1780 non-desert counties.

[26] Newspaper closures and mergers are associated with poorer information quality and many adverse corporate outcomes (Kyung & Nam, 2023; Heese et al., 2022; Jiang & Kong, 2024; Leonelli, 2024; Ma et al., 2025; Gao et al., 2020) but are not primarily driven by local economic decline (Ma et al., 2025). We obtain data on local newspaper closures and mergers from UNC's Center for Innovation and Sustainability in Local Media. We consider multiple events in the same county and year as one, keep the first treatment event in each county, and restrict our sample to the 27 counties that experienced at least one such event.

[27] We source data on the number of newspaper establishments from the Quarterly Census of Employment and Wages to construct an indicator for counties in the bottom tercile of newspaper establishments (Allee et al., 2025).

might also shift toward more attractive loan terms that are less profitable for the bank.

To examine the likelihood of this supply-side alternative, we estimate the following OLS model at the bank-county-year level:

$$Loan\ Amount_{tbc} = \beta_0 + \beta_1 EDO\ Cohort_{tb} + \gamma_1 Bank_{(t-1)b} + \gamma_2 Econ_{(t-1)c} + \eta_c + \alpha_b + \delta_t + \varepsilon_{tbc}\ , \tag{8}$$

where *Loan Amount* is the total amount of loans issued by a bank in a county-year.[28] Results presented in Table 9 Panel A show that EDO banks in fact contract lending during EDOs relative to control banks, inconsistent with a supply-side credit expansion driving the observed shift towards lower-quality borrowers. Moreover, we also test whether EDO banks change their loan terms when controlling for borrower credit quality. We reestimate Equation 8 replacing *Loan Amount* with the following loan characteristics: the imputed APR (*Interest Rate*), loan size (*Loan Size*), and initial loan term (*Loan Length*). We include *Credit Score* and *Borrower Age* to capture and control for borrower quality. Results presented in Table 9 Panel B show insignificant and negligible changes in interest rates and loan size but a significant decrease in loan length during EDOs. Specifically, Columns (5) and (6) indicate that loan length decreases by 1.7–2.9% in the *During EDO* period, which translates into a modest 1–2 month decrease relative to the *Pre EDO* average length of 57 months. Taken together, EDO banks did not expand total lending or make their loan terms more attractive, suggesting that supply-side changes do not drive the decline in loan quality we observe during EDOs.

5.2. Borrower financial sophistication

If a decline in trust drives borrowers' decisions, our results should be concentrated among borrowers who are more financially sophisticated, as they are more likely to consider bank misconduct in their borrowing decisions. We use geographic variation in education levels to proxy for financial sophistication (Forman et al., 2012; Kumar, 2009) and reestimate

[28] Note that we only have a 10% random sample of loans from TransUnion and this sample is not stratified by bank. Thus, this test is an approximation of the change in total lending by each bank.

Equation 7 replacing *News Desert* with *High Education*, an indicator of whether a census tract is within the top tercile of the proportion of high school-, college-, or postbaccalaureate-educated individuals.[29] Consistent with our main findings, Table IA6 shows that, in financially sophisticated areas, loans originated during an EDO become delinquent sooner than loans originated by control banks. In census tracts with lower financial sophistication, there is no corresponding effect. Moreover, the insignificant $EDO \times High\ Education$ coefficient does not indicate that EDO banks systematically operate in high-education areas. These results suggest that EDOs result in greater reputational damage and deterioration of trust in financially sophisticated areas.

5.3. EDO severity

More severe EDOs attract greater attention, as they are more likely to be covered by news outlets or communicated informally by word of mouth. Thus, we should observe a greater decline in borrower quality for these EDOs. We proxy for severity using EDO length, as more severe EDOs generally take longer to resolve (An et al., 2024; Kleymenova & Tomy, 2022). We reestimate Equation 7 replacing *News Desert* with *Long EDO*, an indicator for whether an EDO is four years or longer (approximately the 80th percentile among all EDOs).[30] Consistent with our expectation, the results in Table IA7 show that, for long EDOs, loans originated in the *During EDO* period are of lower quality compared to loans originated by control banks. These results are consistent with more severe EDOs inducing greater reputational damage to sanctioned banks, resulting in greater declines in trust.

[29] Regions with more financially sophisticated populations are often wealthier. Although we control for the unemployment rate and annual per capita income growth in our estimations, we recognize that our measures of financial sophistication may still reflect underlying wealth differences.

[30] This analysis relies solely on the EDO bank sample, so we do not use entropy balancing. Moreover, as *Long EDO* is defined only within this sample, we capture only within-EDO bank temporal variation.

6. Discussion and conclusion

Trust in banks has fallen significantly since the financial crisis of 2007–2009, and this deterioration of trust has become relevant again after the collapse of Silicon Valley Bank. While prior literature has studied the determinants of such trust, much less work explores the consequences of declining trust, especially its impact on consumers' financial decisions. The limited work focuses on depositors, but trust in banks is also important for borrowers, who are also vital to the health of the banking sector. In this paper, we study how retail borrowers respond to a negative shock to trust: enforcement actions issued against individual banks.

We combine publicly-disclosed enforcement actions with granular loan and borrower data from a credit reporting agency to study how declining trust in banks affects retail borrowers. We find a downward shift in the quality of new loans and borrowers during enforcement actions. This suggests that higher-quality borrowers, who have more outside options for credit and are likely more sensitive to perceived changes in service quality, avoid transacting with sanctioned banks. Consistent with trust spillovers that extend beyond the institutions responsible for misconduct, we find that greater exposure to sanctioned banks is associated with declining borrower and loan quality at non-EDO banks and improved quality at nonbank financial institutions.

Several additional results support the trust mechanism. First, sanctioned banks are less likely to see repeat borrowers, suggesting that enforcement actions disrupt trust-based lending relationships. Second, enforcement actions are associated with significant declines in survey-based measures of trust in banks and bankers. Moreover, the shift towards lower-quality borrowers during enforcement occurs only when such trust declines. Third, our results are concentrated in regions with negative sentiment in local news articles covering enforcement actions. Fourth, our results do not hold in regions with little or no local newspaper coverage, where consumers are less likely to be aware of enforcement actions.

Finally, we provide evidence inconsistent with the possibility that supply-side effects, including banks expanding credit to lower-quality borrowers or providing more attractive loan terms, drive the decline in borrower quality during enforcement. On the contrary, sanctioned banks contract lending and, conditional on borrower quality, exhibit no material changes in interest rates or loan sizes.

Our work extends the literature on the effect of trust in banks on consumers' financial choices to the retail borrowing context. Future research can build on these insights by examining broader economic implications of declining trust, such as its impact on local economic growth, credit markets, or employment. More broadly, future work could also investigate how other stakeholders, including regulators and businesses, respond to changes to trust in banks and other institutions.

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Appendix A. Variable definitions

Variable	Definition	Source
Dependent Variables		
Bankruptcy	Indicator variable equal to 1 if the borrower has ever had a tradeline bankruptcy, lagged by one month.	TransUnion
Collections	Indicator variable equal to 1 if the borrower has ever had a loan in collections, lagged by one month.	TransUnion
Credit Score	Natural log of the VantageScore 3.0 of the borrower (scale of 300 to 850), lagged by one month and winsorized at the 1st and 99th percentile by loan origination year. (Also a control variable.)	TransUnion
Defaults	Indicator variable equal to 1 if the borrower has ever had a loan more than 90 days past due, lagged by one month.	TransUnion
Delinquent	Indicator variable equal to 1 if the loan ever becomes delinquent.	TransUnion
Interest Rate	Annual Percentage Rate (APR) charged on the loan, imputed from loan amount, loan length, and monthly payment amount, winsorized at the 1st and 99th percentile by loan origination year.	Calculation
Loan Amount	Natural log of the total amount of auto loans issued by a bank in a county-year, winsorized at the 1st and 99th percentile by loan origination year.	TransUnion
Loan Length	Natural logarithm of the number of months of the initial loan, winsorized at the 1st and 99th percentile by loan origination year.	TransUnion
Loan Size	Natural logarithm of the highest amount ever owed on the loan (initial loan amount), winsorized at the 1st and 99th percentile by loan origination year.	TransUnion
Past Due (12mo)	Natural log of the borrower's total past due amount in the past 12 months, lagged by one month and winsorized at the 1st and 99th percentile by loan origination year.	TransUnion
Repeat	Indicator variable equal to 1 if the loan is not the consumer's first loan from the same bank.	TransUnion

Time to Delinquency	Number of months until the manner of payment for the loan is no longer "paid or paying as agreed". Calculated implicitly in the survival model from a variable indicating first month of delinquency.	TransUnion
Trust (Bankers)	Indicator variable equal to 1 if the average response in a county-year to the question "How much do you trust bankers?" is 4 or higher on a 1-5 scale, where 1 means "I do not trust them at all" and 5 means "I trust them completely."	Chicago Booth/Kellogg School Financial Trust Index
Trust (Banks)	Indicator variable equal to 1 if the average response in a county-year to the question "How much do you trust banks?" is 4 or higher on a 1-5 scale, where 1 means "I do not trust them at all" and 5 means "I trust them completely."	Chicago Booth/Kellogg School Financial Trust Index
% Delinquent	Percent of the borrower's loans ever delinquent, lagged by one month.	TransUnion
Independent Variables		
EDO	Indicator variable equal to 1 if loan is originated by an EDO bank.	SNL
Exposure to EDO	The amount of loans issued by EDO banks while an EDO is open divided by the total amount of loans in a given county-year.	TransUnion and SNL
During EDO	Indicator variable equal to 1 if loan is originated while the lender experiences an EDO.	SNL
During EDO 1	Indicator variable equal to 1 if loan is originated in the first year in which the lender experiences an EDO.	SNL
During EDO 1+	Indicator variable equal to 1 if loan is originated in any year following the first year of EDO while the EDO is still in effect.	SNL
High Exposure to EDO	Indicator variable equal to 1 if a county's *Exposure to EDO* falls in the top tercile in a given year year.	TransUnion and SNL
Post EDO	Indicator variable equal to 1 if loan is originated in the 5 years after the lender experiences an EDO.	SNL
Pre EDO	Indicator variable equal to 1 if loan is originated in the 3 years before the lender experiences an EDO.	SNL
Bank Controls		
Capital Ratio	Total equity divided by total assets for the lender, lagged by one year and expressed in deciles (1 to 10).	Call Reports

Liquidity	Cash and cash equivalents divided by total assets for the lender, where cash is defined as the sum of interest-bearing balances, noninterest-bearing balances, and currency and coin, lagged by one year and expressed in deciles (1 to 10).	Call Reports
NPA	Accruing and nonaccruing loans in the past 90 days divided by net total loans for the lender, lagged by one year and expressed in deciles (1 to 10).	Call Reports
ROA	Net income divided by total assets for the lender, lagged by one year and expressed in deciles (1 to 10).	Call Reports
Size	Natural logarithm of the lender's total assets, lagged by one year and expressed in deciles (1 to 10).	Call Reports
Economic Controls		
PC Income Growth	One-year growth in per-capita income at the census-tract level, lagged by one year and winsorized at the 1st and 99th percentile by loan origination year.	ACS
Unemployment Rate	Unemployment rate at the census-tract level, lagged by one year and winsorized at the 1st and 99th percentile by loan origination year.	ACS
Additional Economic Controls		
Median Age	Natural logarithm of median age at the census-tract level, lagged by one year and winsorized at the 1st and 99th percentile by loan origination year.	ACS
PC Income	Natural logarithm of per-capita income at the census-tract level, lagged by one year and winsorized at the 1st and 99th percentile by loan origination year.	ACS
Population	Natural logarithm of population at the census-tract level, lagged by one year and winsorized at the 1st and 99th percentile by loan origination year.	ACS
Urbanization	Urban population divided by total population at the census tract level in 2010.	2010 Census
Other Controls		
Borrower Age	Natural logarithm of the borrower's age at loan origination, winsorized at the 1st and 99th percentile by loan origination year.	TransUnion

Cross-Sectional Variables

Decline in Trust (Dummy)	Indicator variable equal to 1 if *Decline in Trust (Percentage)* is positive.	Chicago Booth/Kellogg School Financial Trust Index
Decline in Trust (Percentage)	County-level changes in the average trust in banks between the year before and the year after the issuance of EDO against a given bank, aggregated across all counties where the bank issues loans and computed as a percentage change relative to the pre-EDO average trust.	Chicago Booth/Kellogg School Financial Trust Index
High Education (College)	Indicator variable equal to 1 if borrower resides in a census tract which is in the top tercile of average college graduation in the US one year before the loan origination.	ACS
High Education (High School)	Indicator variable equal to 1 if borrower resides in a census tract which is in the top tercile of average high school graduation in the US one year before the loan origination.	ACS
High Education (Postbacc.)	Indicator variable equal to 1 if borrower resides in a census tract which is in the top tercile of average postbaccalaureate graduation in the US.	ACS
Long EDO	Indicator variable equal to 1 if an EDO is in effect for four years or longer.	SNL
Low Establishment Count	Indicator variable equal to 1 if borrower resides in a county which is in the bottom tercile of the number of newspaper publishing establishments in the US one year before the loan origination.	BLS-QCWE
Low Income (Household)	Indicator variable equal to 1 if borrower resides in a census tract which is in the bottom tercile of median household income one year before the loan origination.	ACS
Low Income (Individual)	Indicator variable equal to 1 if borrower resides in a census tract which is in the bottom tercile of median individual income one year before the loan origination.	ACS
Low Trust (Hayes et al.)	Indicator variable equal to 1 if the borrower resides in a state with below-median ex ante trust as measured by ancestral trust from Hayes et al. (2021)	Hayes et al. (2021)
Negative Sentiment	State-year average of the continuous article-level negative sentiment score.	Authors' calculation
News Desert	Indicator variable equal to 1 if borrower resides in a county without a local newspaper in 2004.	UNC

Positive Sentiment	State-year average of the continuous article-level positive sentiment score.	Authors' calculation
Post Newspaper Closure	Indicator variable equal to 1 if an EDO is issued after a county experiences a newspaper closure and/or merger.	UNC
Trust Sentiment	State-year average of the continuous article-level trust emotion score.	Authors' calculation

Appendix B. Local news coverage examples

Example 1. FDIC Enforcement Action on Ohana Pacific Bank

Unsafe practices prompt FDIC alert to isle bank
Honolulu Star-Bulletin – December 2, 2009

Bank regulators have ordered Ohana Pacific Bank, which opened in 2006 and caters primarily to Hawaii's Korean community, to shore up capital, improve asset quality and maintain adequate liquidity levels.

Ohana Pacific Bank has agreed to a formal enforcement action with the Federal Deposit Insurance Corp. and the Hawaii Department of Financial Institutions.

In a cease-and-desist order made public on Friday, FDIC and the state agency said thebank's managers and board of directors failed to provide adequate supervision. Among the unsafe banking practices cited were inadequate capital, inadequate loan valuation and poor-quality loans.

"Ohana Pacific Bank has started to work toward full compliance with the enforcement action and has already developed and initiated a number of programs to this end," the company said in a press release.

The bank will continue to provide customers with a full range of deposit and loan products, the company said. (...)

Example 2. Federal Reserve Enforcement Action on Liberty Bank

Larry Woods, president of banks in Boulder Creek, Felton retires; Philip LaChapelle replaces him
Santa Cruz Sentinel – December 6, 2011

New leadership has taken over at Liberty Bank, a bank with offices in Boulder Creek, Felton and Palo Alto that has been under scrutiny by state and federal regulators since March because of problem loans. (...)

Woods signed a regulatory agreement Oct. 25 with the Federal Reserve Bank of San Francisco, which called for the board of directors to submit a plan to the Federal Reserve Bank within 60 days to "strengthen board oversight of the management and operations." (...)

A week later, Woods told the Sentinel that he had hired additional bank staff and they were "working diligently" to correct problems identified by regulators. (...)

Example 3. FDIC Enforcement Action on Chambers Bank

Lender hit with federal sanction - Danville bank
Arkansas Democrat-Gazette – January 28, 2012

Chambers Bank of Danville, which lost almost $18 million in 2010, has been sanctioned by the Federal Deposit Insurance Corp., the regulator said Friday.

The order was issued against the bank Dec. 21, but not released until Friday.

The bank, which has about $720 million in assets, has experienced lending problems with the real estate market in Northwest Arkansas, said John Chambers, the bank's chief executive officer.

"Without question, the real estate market in Northwest Arkansas has been in a downward spiral since sometime in 2007," Chambers said. "We have been cleaning those wounds since." (...)

Example 4. OCC Enforcement Action on Westbury Bank

Official orders fixes for Westbury Bank
Milwaukee Journal Sentinel – December 22, 2012

Westbury Bank, which said in October it plans to go public with a $46.3 million stock offering, has been told by a regulator to boost capital, address bad loans and take other steps to improve the bank.

In a written agreement with Westbury, the Office of the Comptroller of the Currency said it has found "unsafe and unsound banking practices" related to management, credit risk management and inadequate loan-loss reserves, as well as violations of law, at the West Bend-based bank.

As part of the agreement, Westbury is designated as being in "troubled condition," although regulatory records show its capital ratios have improved this year and that it had a profit of $630,000 through Sept. 30.

Westbury lost $7.5 million in 2011 and $1.3 million in 2010. (...)

Example 5. FDIC Enforcement Action on Mid America Bank

FDIC, State puts limits on Mid America Bank
Wisconsin State Journal – April 26, 2013

Mid America Bank has agreed to a consent order with the Federal Deposit Insurance Corp. and the Wisconsin Department of Financial Institutions mandating the Janesville bank to take a series of steps.

Under terms of the order, signed March 15 and disclosed this week, Mid America has to hire an outside consultant to conduct a management study determining how to "restore all aspects of the bank to a safe and sound condition."

Other requirements include creating an ethics policy and providing ethics training at least once a year; reducing the bank's risk position for all delinquent loans of more than $200,000; maintaining a total risk-based capital ratio of at least 13 percent; and not increasing assets by more than 5 percent or loans by more than 10 percent during a three-month period without government approval. Dividends to shareholders also are barred without FDIC approval. (...)

Example 6. Federal Reserve Enforcement Action on Fulton Financial Corp.

Fulton Financial gets Fed cease and desist order
Central Penn Business Journal – September 12, 2014

Fulton Financial Corp. knew it was coming, and this week, it came.

The Lancaster-based bank parent company of Fulton Bank received a cease-and-desist order from the Board of Governors of the Federal Reserve concerning one of its other subsidiaries, Lafayette Ambassador Bank of Bethlehem.

The order is for Fulton to comply with certain new standards and regulations within the banking industry. In a news release, Fulton said it intends to comply.

In July, the company received similar orders for three of its other subsidiary banks — Fulton, Swineford and FNB Bank. The orders were to "strengthen and enhance" their compliance with the Bank Secrecy Act and anti- money-laundering compliance programs. (...)

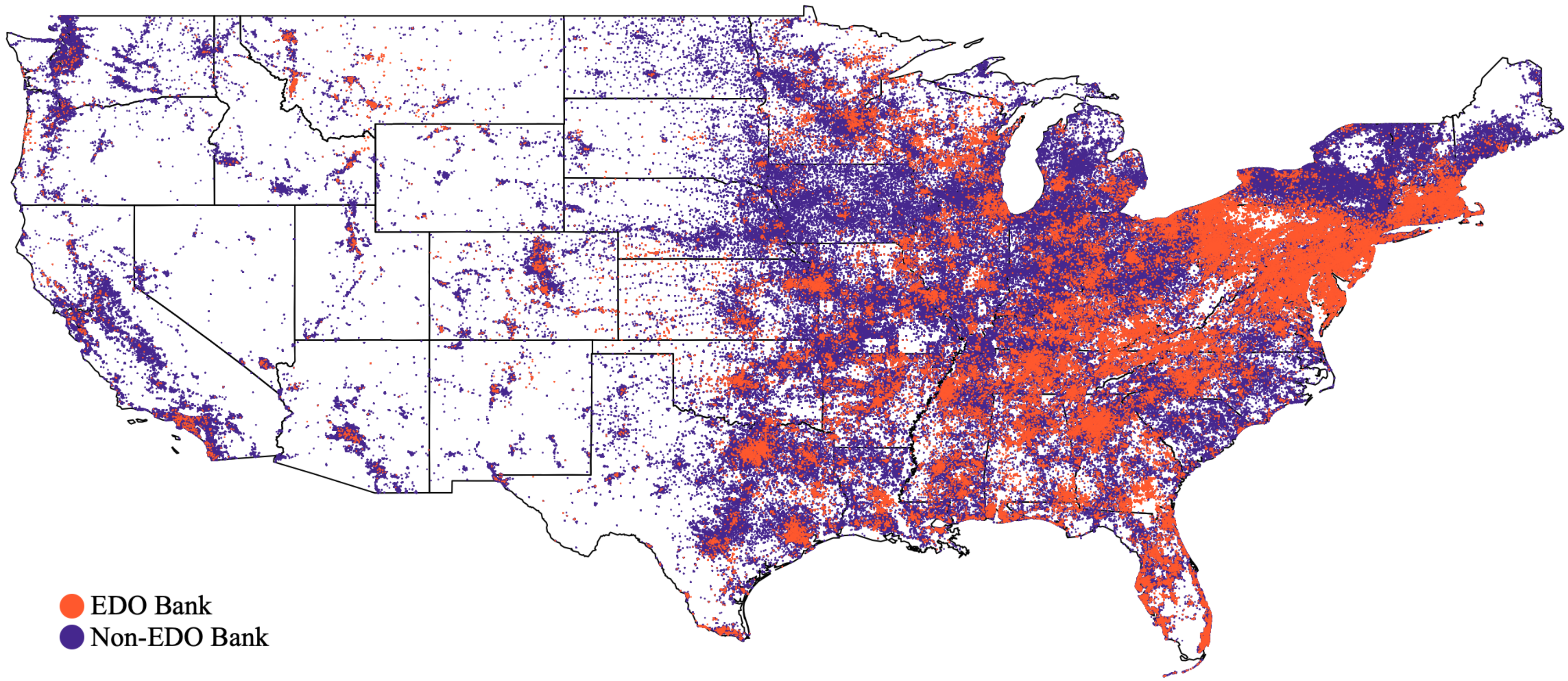


Figure 1: Geographic distribution of EDO and non-EDO auto loans

This figure shows the geographic distribution of auto loans by the lending bank's EDO status across the contiguous United States. When overlapping, EDO loans are plotted over non-EDO loans.

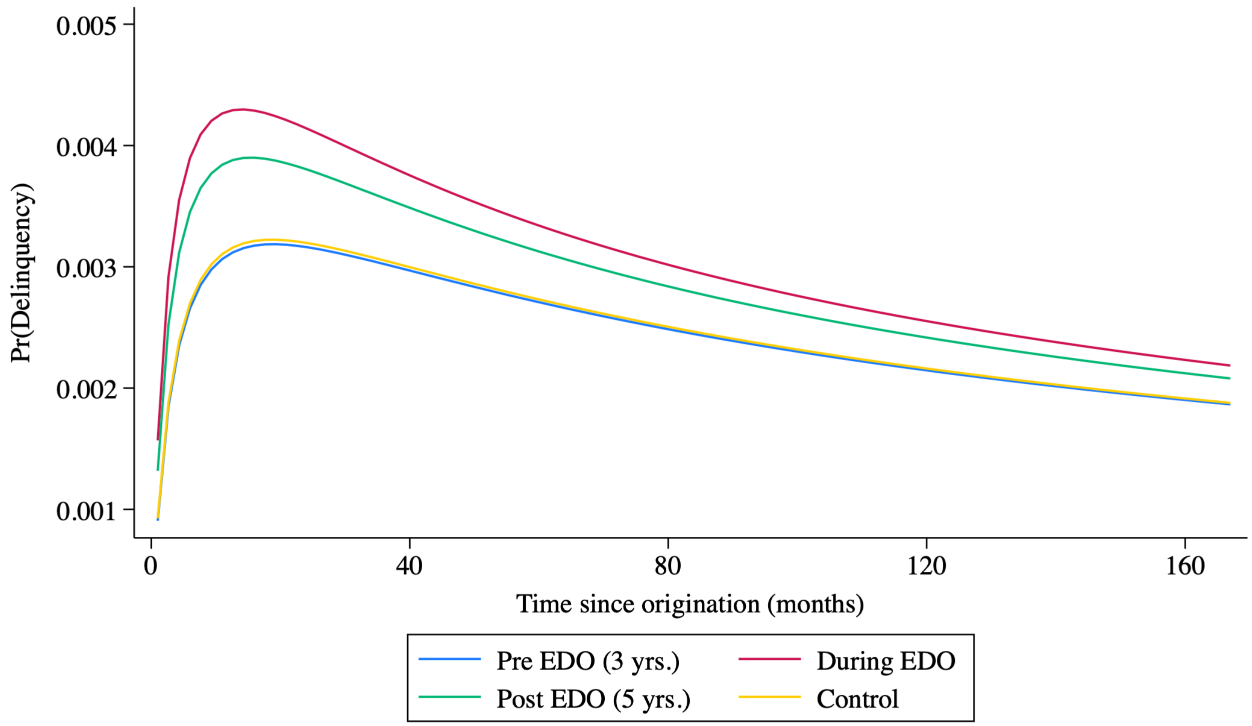


Figure 2: Time to delinquency by *EDO Cohort*

This figure shows the change in probability of delinquency over the life of auto loans by *EDO Cohort*. We estimate the model from Column (1) of Table 2 and graph the average probability of delinquency of loans over months of age for each aggregate cohort. All variables are defined in Appendix A.

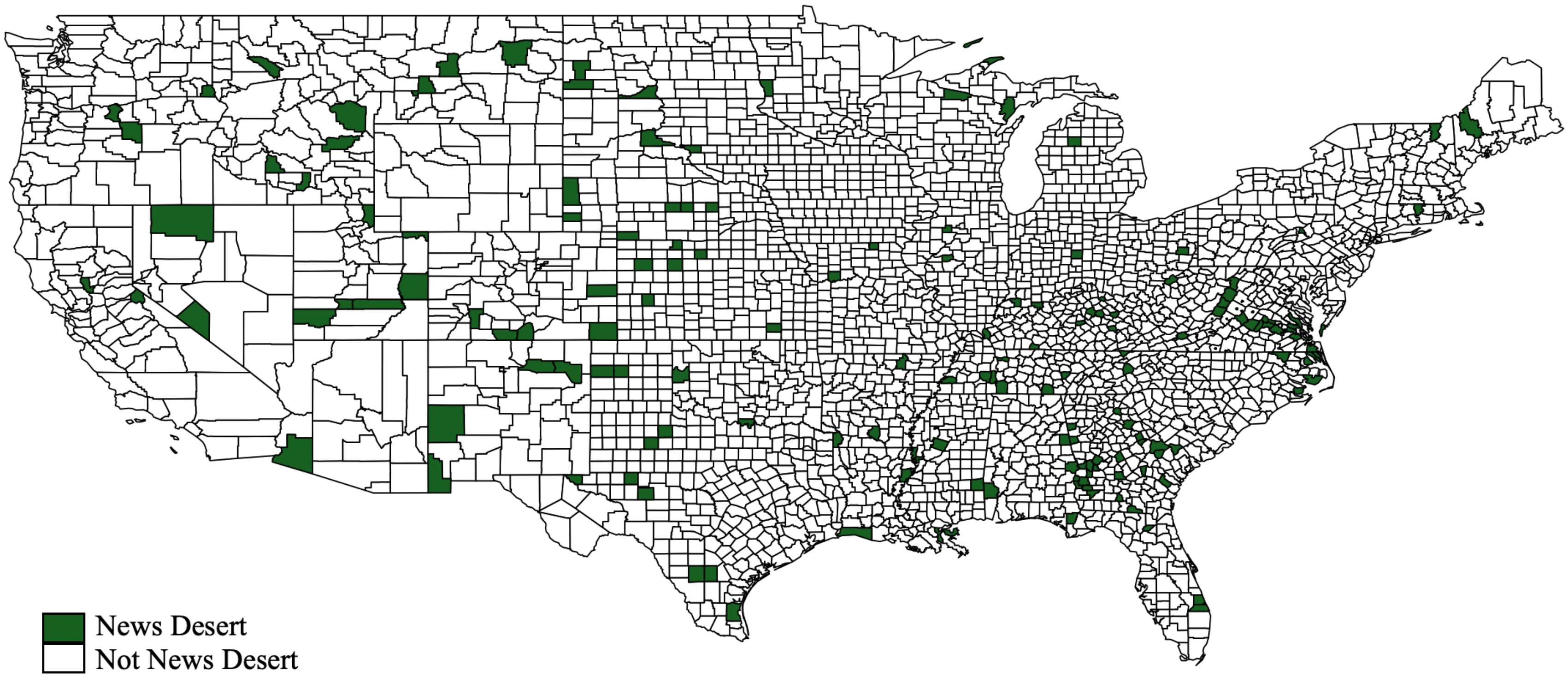


Figure 3: Geographic distribution of news deserts

This figure shows the geographic distribution of news deserts across the contiguous United States.

Table 1: Descriptive statistics

This table presents the descriptive statistics for the sample we use in our analyses. In panel A, the summary statistics are presented at the *loan level* whenever possible for ease of interpretation. *Loan Amount*, *Trust (Banks)*, and *Trust (Bankers)* are presented at the level of analysis. Panel B compares characteristics of the EDO and non-EDO banks included in our analyses. These are presented at the *bank level* for ease of interpretation. All variables are defined in Appendix A.

Panel A: Summary statistics

Variable	Obs	Mean	Std. Dev.	P1	P25	Median	P75	P99
Dependent Variable (Lognormal AFT Model)								
Time to Delinquency	159,461	20.128	15.420	3.000	8.000	16.000	28.000	69.000
Dependent Variables (OLS Model)								
Delinquent	1,832,305	0.087	0.282	0.000	0.000	0.000	0.000	1.000
Credit	1,832,305	6.524	0.173	5.704	6.463	6.553	6.636	6.719
Collections	1,832,305	0.192	0.394	0.000	0.000	0.000	0.000	1.000
Defaults	1,832,305	0.260	0.439	0.000	0.000	0.000	1.000	1.000
Bankruptcy	1,832,305	0.034	0.182	0.000	0.000	0.000	0.000	1.000
% Delinquent	1,832,305	9.818	17.203	0.000	0.000	0.000	13.000	80.000
Past Due (12mo)	1,832,305	0.569	1.951	0.000	0.000	0.000	0.000	9.016
Loan Amount	246,274	10.576	1.465	7.601	9.569	10.428	11.498	14.432
Interest Rate	1,735,674	0.064	0.035	0.017	0.038	0.055	0.080	0.180
Loan Amount	1,831,828	9.586	0.782	7.372	9.132	9.714	10.151	10.944
Loan Length	1,825,748	3.933	0.483	2.079	3.871	4.094	4.277	4.431
Trust (Banks)	10,713	0.298	0.457	0.000	0.000	0.000	1.000	1.000
Trust (Bankers)	10,645	0.224	0.417	0.000	0.000	0.000	0.000	1.000
Independent Variables								
EDO	1,832,305	0.076	0.265	0.000	0.000	0.000	0.000	1.000
Pre EDO	1,832,305	0.014	0.120	0.000	0.000	0.000	0.000	1.000
During EDO	1,832,305	0.027	0.162	0.000	0.000	0.000	0.000	1.000
During EDO 1	1,832,305	0.006	0.077	0.000	0.000	0.000	0.000	0.000
During EDO 1+	1,832,305	0.021	0.144	0.000	0.000	0.000	0.000	1.000
Post EDO	1,832,305	0.030	0.170	0.000	0.000	0.000	0.000	1.000
Bank Controls								
Size	1,832,305	7.698	2.270	0.000	7.000	9.000	9.000	9.000
ROA	1,832,305	4.889	2.615	0.000	3.000	5.000	7.000	9.000
Liquidity	1,832,305	4.110	3.080	0.000	1.000	4.000	7.000	9.000
NPA	1,832,305	4.968	2.149	0.000	3.000	6.000	7.000	9.000
Capital Ratio	1,832,305	3.901	2.702	0.000	1.000	4.000	6.000	9.000
Economic Controls								
PC Income Growth	1,832,305	0.022	0.061	-0.124	-0.016	0.020	0.057	0.191
Unemployment Rate	1,832,305	0.071	0.040	0.010	0.041	0.063	0.091	0.201
Additional Economic Controls								
Population	1,832,305	8.450	0.432	7.352	8.176	8.469	8.737	9.511
PC Income	1,832,305	10.397	0.338	9.649	10.170	10.371	10.602	11.307
Median Age	1,832,305	3.684	0.167	3.170	3.584	3.706	3.800	4.025
Urbanization	1,832,283	0.630	0.422	0.000	0.078	0.880	1.000	1.000
Other Controls								
Borrower Age	1,788,436	3.766	0.343	3.045	3.497	3.807	4.025	4.382
Cross-Sectional Variables								
Repeat	1,832,305	0.296	0.456	0.000	0.000	0.000	1.000	1.000
Decline in Trust (Dummy)	1,778,498	0.051	0.220	0.000	0.000	0.000	0.000	1.000
Decline in Trust (Percentage)	1,778,498	-0.001	0.091	-0.117	0.000	0.000	0.000	0.071
Low Trust (Hayes et al.)	1,832,305	0.550	0.498	0.000	0.000	1.000	1.000	1.000
Trust Sentiment	1,829,312	0.242	0.065	0.099	0.202	0.241	0.269	0.429
Negative Sentiment	1,829,312	0.120	0.046	0.000	0.096	0.127	0.144	0.231
Positive Sentiment	1,829,312	0.265	0.061	0.000	0.228	0.264	0.306	0.422
News Desert	1,832,305	0.016	0.127	0.000	0.000	0.000	0.000	1.000

Panel B: Comparison of EDO and Non-EDO Banks

Bank Controls	EDO Banks		Non-EDO Banks		t-test	
	N	Mean	N	Mean	Difference	p-value
Size	534	4.612	2,326	4.371	0.242*	0.071
ROA	534	3.197	2,326	4.809	-1.613***	0.000
Liquidity	534	4.814	2,326	4.342	0.472***	0.000
NPA	534	5.954	2,326	4.214	1.740***	0.000
Capital Ratio	534	3.976	2,326	4.666	-0.69***	0.000

Table 2: Time to delinquency for EDO banks

This table shows the effect of EDOs on auto loan delinquencies. Columns (1)–(2) are estimated using a lognormal survival (AFT) model. Column (1) is estimated using the unmatched sample, while Columns (2) and (3) is estimated using the entropy balanced sample. The dependent variable is *Time to Delinquency*. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency		
	(1)	(2)	(3)
EDO	0.032	0.202	0.202
	(0.193)	(1.283)	(1.264)
Pre EDO	-0.017	-0.091	-0.091
	(-0.170)	(-1.206)	(-1.205)
During EDO	-0.324*	-0.309*	
	(-1.702)	(-1.785)	
During EDO 1			-0.316***
			(-2.683)
During EDO 1+			-0.307
			(-1.523)
Post EDO	-0.236	-0.300	-0.300
	(-1.154)	(-1.507)	(-1.469)
PC Income Growth	-0.198***	-0.105	-0.105
	(-4.280)	(-1.146)	(-1.150)
Unemployment Rate	-4.130***	-3.296***	-3.297***
	(-9.977)	(-10.784)	(-10.882)
Size	0.136***	0.102***	0.102***
	(7.814)	(6.820)	(6.812)
ROA	-0.000	-0.015	-0.015
	(-0.029)	(-1.108)	(-1.101)
Liquidity	0.039**	0.004	0.004
	(2.383)	(0.247)	(0.240)
NPA	-0.016	-0.036***	-0.036***
	(-0.908)	(-2.586)	(-2.601)
Capital Ratio	-0.047***	-0.027*	-0.027*
	(-2.784)	(-1.698)	(-1.700)
Observations	47,247,006	47,247,006	47,247,006
Wald χ^2	18012***	17046***	17246***
Year-Month FE	Yes	Yes	Yes
Strata	State	State	State
Model	AFT	AFT	AFT

Table 3: Changes in borrower composition during EDOs

This table shows changes in borrower characteristics over the various stages of an EDO, utilizing the entropy-balanced sample. The odd columns include year-month, bank, and county fixed effects, whereas the even columns replace year-month and county fixed effects with county × year-month fixed effects. The dependent variables are various elements of borrower credit quality and history. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Credit Score		*Collections*		*% Delinquent*		*Past Due (12mo)*		*Defaults*		*Bankruptcy*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pre EDO	-0.002	-0.007**	0.016	0.033***	0.115	0.943*	0.036	0.120**	0.009	0.009	0.003	0.002
	(-0.555)	(-2.004)	(0.889)	(2.686)	(0.187)	(1.881)	(0.676)	(2.459)	(0.543)	(0.749)	(0.827)	(0.457)
During EDO	-0.008**	-0.009**	0.035**	0.035**	0.938*	1.249**	0.100**	0.114**	0.030**	0.010	0.009***	0.004
	(-2.080)	(-2.463)	(2.122)	(2.457)	(1.793)	(2.060)	(1.998)	(2.190)	(2.112)	(0.724)	(2.758)	(0.940)
Post EDO	-0.002	-0.007	0.026	0.035*	0.484	1.207	0.041	0.087	0.017	0.006	0.009*	0.004
	(-0.403)	(-1.226)	(1.465)	(1.767)	(0.798)	(1.302)	(0.750)	(1.066)	(1.070)	(0.269)	(1.820)	(0.789)
Borrower Age	0.100***	0.100***	-0.030***	-0.032***	-2.532***	-2.547***	-0.003	-0.001	0.024***	0.025***	0.032***	0.033***
	(24.292)	(27.580)	(-4.350)	(-5.322)	(-5.838)	(-6.587)	(-0.124)	(-0.070)	(3.416)	(3.520)	(15.678)	(14.279)
Observations	1,788,295	1,720,318	1,788,295	1,720,318	1,788,295	1,720,318	1,788,295	1,720,318	1,788,295	1,720,318	1,788,295	1,720,318
Adjusted R^2	0.216	0.332	0.147	0.276	0.110	0.238	0.105	0.233	0.090	0.220	0.035	0.175
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
County × Year-Month FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Model	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Table 4: Spillover effects on loan quality and borrower characteristics

This table examines the spillover effects of EDOs to non-EDO banks and non-banks. Panel A investigates the effect of exposure to EDO banks on loan quality. Column (1) is estimated using the full sample of non-EDO banks, while Column (2) is estimated using a 10% random sample of non-banks. Both columns are estimated using a lognormal survival (AFT) model. The dependent variable is *Time to Delinquency*. Panel B (Panel C) examines the effect of exposure to EDO banks on borrower characteristics using the full sample of non-EDO banks (a 10% random sample of non-banks). In both panels, Columns (1)–(6) are estimated using an OLS model and include year-month, bank, and county fixed effects. The dependent variables are various elements of borrower credit quality and history. All standard errors are clustered at the county level. All variables are defined in Appendix A. The z-statistics (t-statistics) are presented in parentheses in Panel A (Panels B and C); $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

Panel A: Exposure to EDO banks and loan quality

	Time to Delinquency	
	Non-EDO Banks (1)	Non-Banks (2)
Exposure to EDO	-0.101 (-1.420)	0.073** (2.120)
Observations	43,141,846	113,863,875
Wald χ^2	12504***	31808***
Bank controls	Yes	Yes
Economic controls	Yes	Yes
Year-Month FE	Yes	Yes
Strata	State	State
Model	AFT	AFT

Panel B: Exposure to EDO banks and changes in borrower characteristics for non-EDO banks

	Credit Score	*Collections*	*% Delinquent*	*Past Due (12mo)*	*Defaults*	*Bankruptcy*
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to EDO	-0.015***	0.016	1.522**	0.237***	0.032**	0.000
	(-2.828)	(1.340)	(2.146)	(3.398)	(2.444)	(0.071)
Observations	1,693,230	1,693,230	1,693,230	1,693,230	1,693,230	1,693,230
Adjusted R^2	0.102	0.143	0.099	0.089	0.083	0.026
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS	OLS	OLS

Panel C: Exposure to EDO banks and changes in borrower characteristics for non-banks

	Credit Score	*Collections*	*% Delinquent*	*Past Due (12mo)*	*Defaults*	*Bankruptcy*
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure to EDO	0.001	-0.004	-0.392**	0.032	-0.013***	-0.003
	(1.092)	(-0.924)	(-2.365)	(1.616)	(-3.093)	(-1.400)
Observations	4,060,835	4,060,835	4,060,835	4,060,835	4,060,835	4,060,835
Adjusted R^2	0.273	0.240	0.251	0.184	0.158	0.040
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS	OLS	OLS

Table 5: Changes in Repeated Borrowing

This table shows the effect of EDOs on repeated borrowing. Columns (1)–(2) are estimated using an OLS model. Column (1) includes year-month, bank, and county fixed effects, while Column (2) replaces year-month and county fixed effects with county × year-month fixed effects. The dependent variable is *Repeat*. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Repeat	*Repeat*
	(1)	(2)
Pre EDO	-0.046	-0.042
	(-1.445)	(-1.487)
During EDO	-0.115***	-0.108***
	(-3.045)	(-2.778)
Post EDO	-0.140***	-0.128**
	(-3.106)	(-2.385)
Borrower Age	0.044***	0.046***
	(12.534)	(14.047)
Observations	1,788,295	1,720,318
Adjusted R^2	0.226	0.323
Bank controls	Yes	Yes
Economic controls	Yes	Yes
Year-Month FE	Yes	No
Bank FE	Yes	Yes
County FE	Yes	No
County × Year-Month FE	No	Yes
Model	OLS	OLS

Table 6: Trust and loan quality

This table relates EDOs to survey-based measures of trust in banks (*Trust (Banks)*) and bankers (*Trust (Bankers)*) from the Chicago Booth/Kellogg School Financial Trust Index database. In Panel A, *High Exposure to EDO* is a county-year level measure of exposure to EDO banks based on loans. The economic controls include unemployment rate and yearly percent growth in per capita income. Panel B shows how the decline in trust as well as ex ante trust moderates the effect of EDOs on auto loan delinquencies. Columns (1)–(3) are estimated using a lognormal survival (AFT) model. All standard errors are clustered at the county (bank) level in Panel A (Panel B). All variables are defined in Appendix A. The t-statistics (z-statistics) are presented in parentheses in Panel A (Panel B); $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

Panel A: Exposure to EDOs and trust in banks

	Trust (Banks)		*Trust (Bankers)*	
	(1)	(2)	(3)	(4)
High Exposure to EDO	-0.058***	-0.057***	-0.057***	-0.056***
	(-5.754)	(-5.668)	(-6.441)	(-6.350)
Observations	10,726	10,713	10,658	10,645
Adjusted R^2	0.033	0.033	0.027	0.026
Economic controls	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS

Panel B: Trust and loan quality

	Time to Delinquency		
	Trust: Decline in Trust (Dummy)	Trust: Decline in Trust (Percentage)	Trust: Low Trust (Hayes et al.)
	(1)	(2)	(3)
EDO	-0.205	0.224	-0.068
	(-0.980)	(1.387)	(-0.359)
Pre EDO	-0.182	-0.097	-0.096
	(-1.179)	(-1.230)	(-0.549)
During EDO	0.101	-0.327*	0.131
	(0.548)	(-1.870)	(0.708)
Post EDO	0.085	-0.318	0.206
	(0.387)	(-1.610)	(1.042)
Trust	0.495*	0.433***	-1.548***
	(1.823)	(5.428)	(-3.938)
EDO × Trust			0.302
			(1.304)
Pre EDO × Trust	0.137	-0.016	-0.001
	(0.763)	(-0.210)	(-0.007)
During EDO × Trust	-0.456*	-0.161*	-0.533**
	(-1.731)	(-1.783)	(-2.210)
Post EDO × Trust	-0.379	-0.168	-0.644**
	(-1.099)	(-0.929)	(-2.501)
Observations	47,234,443	47,234,443	47,247,006
Wald χ^2	18696***	20881***	17585***
Bank controls	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Strata	State	State	State
Model	AFT	AFT	AFT

Table 7: Sentiment in the local news coverage of bank enforcement

This table relates EDOs to the sentiment of local media coverage, hand-collected from the NewsBank database. Panel B shows how the sentiment of local media coverage moderates the effect of EDOs on auto loan delinquencies. Columns (1) and (2) examine negative and positive sentiment, respectively, while Column (3) focuses on the sentiment of trust. The dependent variable is *Time to Delinquency*. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The z-statistics (t-statistics) are presented in parentheses in Panel A (Panel B); $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency		
	Sentiment: Negative	*Sentiment: Positive*	*Sentiment: Trust*
	(1)	(2)	(3)
EDO	-0.500*	1.253*	1.023**
	(-1.927)	(1.723)	(2.092)
Pre EDO	0.272	-0.846*	-0.790*
	(0.967)	(-1.832)	(-1.900)
During EDO	0.418	-1.301*	-0.985*
	(1.470)	(-1.682)	(-1.771)
Post EDO	0.537*	-1.090	-1.133**
	(1.942)	(-1.370)	(-2.112)
Sentiment	-0.643*	0.467**	0.177
	(-1.681)	(2.199)	(0.600)
EDO × Sentiment	5.477**	-4.219*	-3.431**
	(2.185)	(-1.658)	(-2.159)
Pre EDO × Sentiment	-2.728	3.091	2.921*
	(-1.284)	(1.631)	(1.750)
During EDO × Sentiment	-5.579**	4.033	2.882
	(-1.973)	(1.503)	(1.627)
Post EDO × Sentiment	-6.623**	3.292	3.484**
	(-2.422)	(1.231)	(2.071)
Observations	46,808,537	46,808,537	46,808,537
Wald χ^2	18632***	18599***	18659***
Bank controls	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Strata	State	State	State
Model	AFT	AFT	AFT

Table 8: Local news environment

This table relates EDOs to local news environment, measured by whether a given county is a news desert. Panel A investigates whether EDOs differentially impacts loan quality based on whether the borrowers reside in a news desert. Columns (1)–(3) are estimated using a lognormal survival (AFT) model and include increasingly stringent control variables and fixed-effects structures. All standard errors are clustered at the bank level. The dependent variable is *Time to Delinquency*. Panel B replicates Table 6 Panel A separately for counties that are news deserts and those that are not. Columns (1)–(4) are estimated using an OLS model. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

Panel A: News deserts and trust in banks

	Trust (Banks)		*Trust (Bankers)*	
	News Desert = 1 (1)	*News Desert* = 0 (2)	*News Desert* = 1 (3)	*News Desert* = 0 (4)
High Exposure to EDO	0.002 (0.040)	-0.057*** (-5.646)	-0.008 (-0.110)	-0.056*** (-6.284)
Observations	236	10,470	233	10,405
Adjusted R^2	0.024	0.034	0.061	0.027
Economic controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	OLS	OLS

Panel B: News deserts and borrower quality

	Time to Delinquency		
	(1)	(2)	(3)
EDO	0.204	0.191	0.190
	(1.293)	(1.198)	(1.193)
Pre EDO	-0.096	-0.084	-0.083
	(-1.247)	(-1.121)	(-1.115)
During EDO	-0.320*	-0.298*	-0.297*
	(-1.853)	(-1.697)	(-1.694)
Post EDO	-0.310	-0.291	-0.290
	(-1.555)	(-1.422)	(-1.420)
News Desert	-0.133	-0.113	-3.463*
	(-1.478)	(-1.264)	(-1.654)
EDO × *News Desert*	-0.106	-0.137	-0.121
	(-0.465)	(-0.606)	(-0.503)
Pre EDO × *News Desert*	0.212	0.224	0.189
	(0.779)	(0.835)	(0.712)
During EDO × *News Desert*	0.616**	0.637***	0.592**
	(2.441)	(2.592)	(2.344)
Post EDO × *News Desert*	0.461*	0.459*	0.411
	(1.728)	(1.720)	(1.506)
During EDO + *During EDO* × *News Desert*	0.297	0.339	0.295
	(1.316)	(1.601)	(1.382)
Observations	47,247,006	45,439,185	45,439,185
Wald χ^2	17434***	18268***	18516***
Bank controls	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes
Additional Economic controls	No	Yes	Yes
News Desert × All Economic controls	No	No	Yes
Year-Month FE	Yes	Yes	Yes
Strata	State	State	State
Model	AFT	AFT	AFT

Table 9: Supply side effects

This table investigates potential supply-side channels through which EDOs could affect loan quality. Panel A shows the effect of EDOs on the amount of loans issued at the extensive margin. This analysis is conducted at the bank-county-year level. The dependent variable is the total amount of loans issued by a bank in a county-year. Column (1) includes year, county, and bank FE, while Column (2) includes county $\times$ year and bank FE. Panel B shows the effect of EDOs on the terms of the auto loans. The dependent variables are interest rate, loan amount, and loan length. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

Panel A: Changes in loan amount at the extensive margin

	Loan Amount	
	(1)	(2)
Pre EDO	-0.018	-0.066
	(-0.389)	(-1.189)
During EDO	-0.132**	-0.202***
	(-2.316)	(-3.342)
Post EDO	-0.106*	-0.166**
	(-1.685)	(-2.497)
Observations	245,965	243,376
Adjusted R-sq	0.248	0.208
Bank controls	Yes	Yes
Economic controls	Yes	No
Year FE	Yes	No
Bank FE	Yes	Yes
County FE	Yes	No
Year $\times$ County FE	No	Yes
Model	OLS	OLS

Panel B: Loan terms

	Interest Rate		*Loan Size*		*Loan Length*	
	(1)	(2)	(3)	(4)	(5)	(6)
Pre EDO	-0.002	-0.001	0.020	0.022	-0.001	-0.005
	(-1.334)	(-0.588)	(1.349)	(1.326)	(-0.058)	(-0.537)
During EDO	-0.002	-0.002	-0.004	-0.016	-0.017*	-0.029***
	(-1.094)	(-1.428)	(-0.281)	(-1.047)	(-1.784)	(-2.804)
Post EDO	-0.002	-0.002	0.017	-0.003	-0.014	-0.023*
	(-1.088)	(-1.293)	(0.846)	(-0.152)	(-1.128)	(-1.677)
Borrower Age	0.000	0.000	-0.044**	-0.029	-0.065***	-0.061***
	(0.503)	(0.059)	(-2.289)	(-1.399)	(-6.473)	(-6.536)
Credit Score	-0.075***	-0.077***	0.470***	0.443***	0.157***	0.135**
	(-11.340)	(-10.185)	(3.971)	(3.680)	(2.713)	(2.396)
Observations	1,693,285	1,623,770	1,693,285	1,623,770	1,693,285	1,623,770
Adjusted R^2	0.424	0.513	0.352	0.458	0.485	0.573
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	No	Yes	No
Year-Month FE	Yes	No	Yes	No	Yes	No
County × Year-Month FE	No	Yes	No	Yes	No	Yes
Model	OLS	OLS	OLS	OLS	OLS	OLS

Internet Appendix

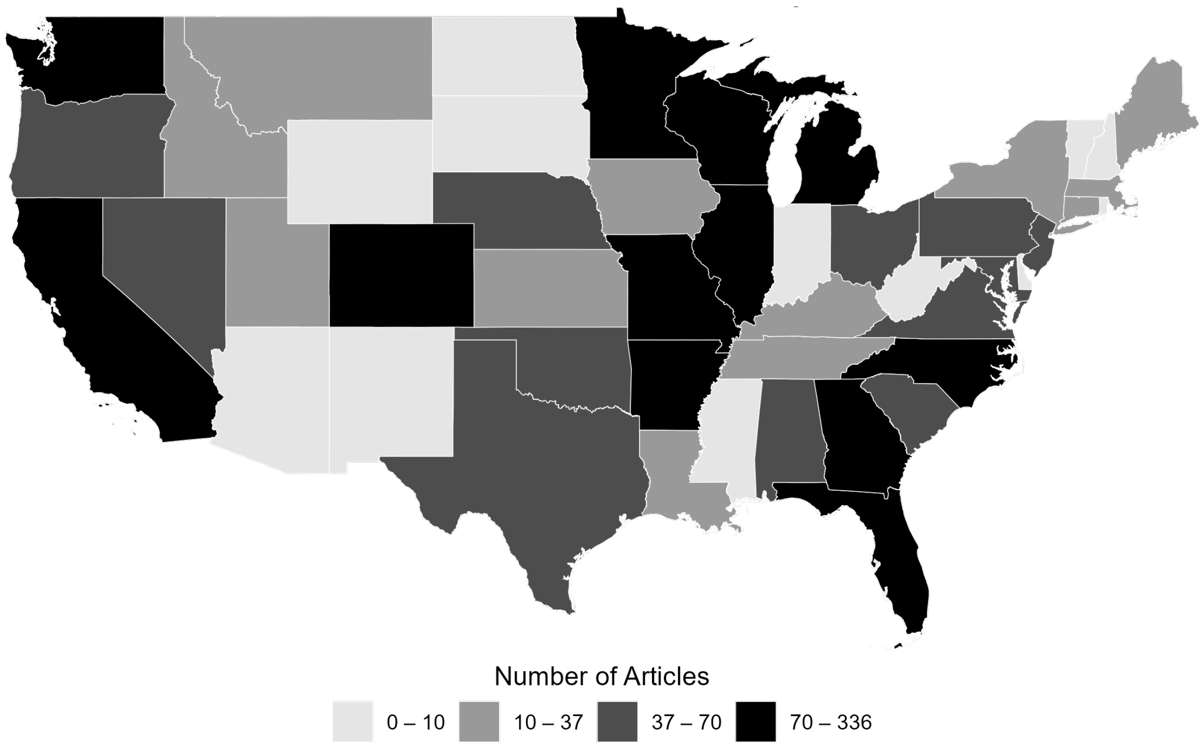
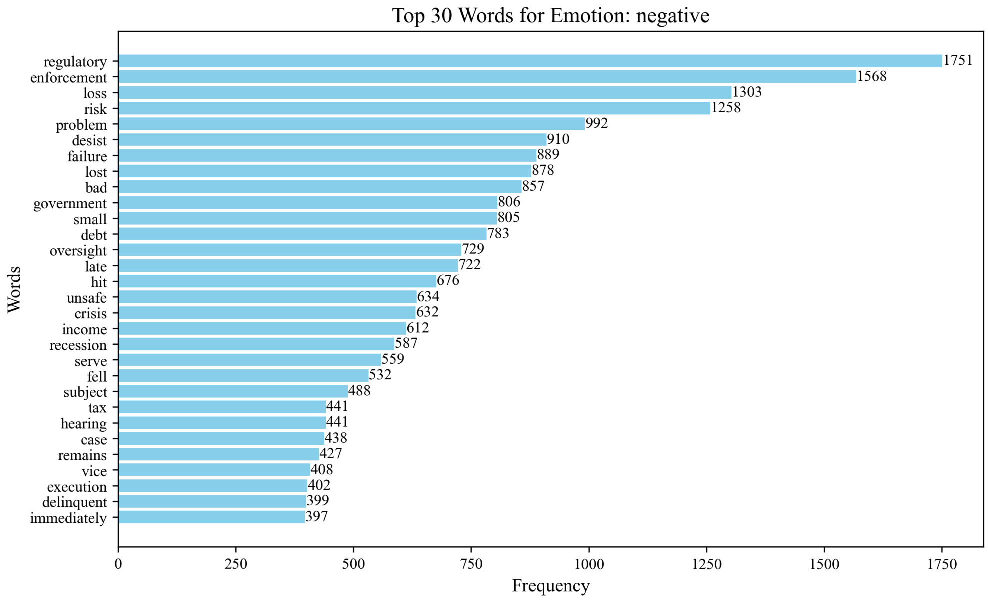
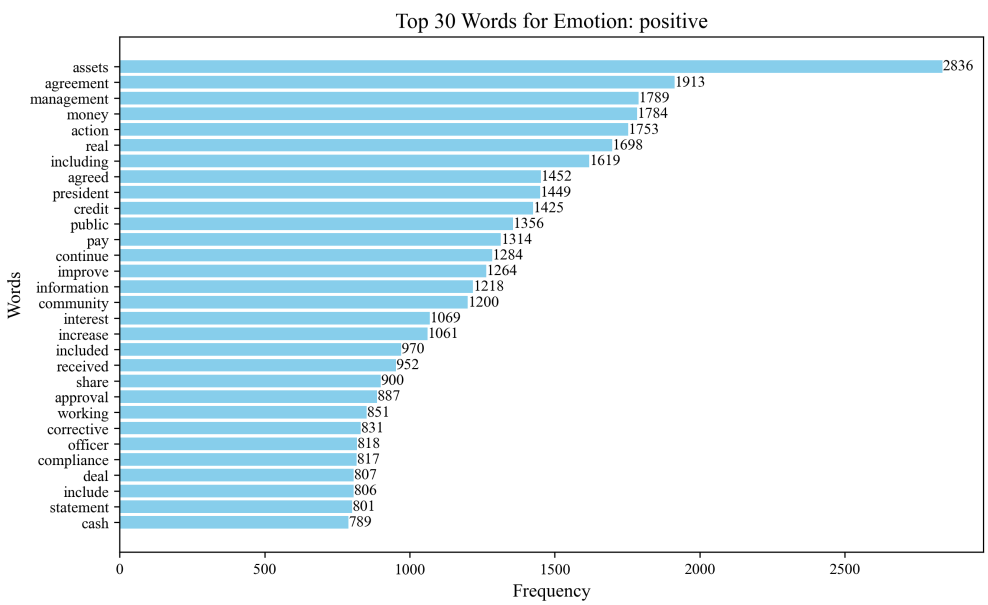


Figure IA1: Geographic distribution of news articles related to EDOs

This figure shows the geographic distribution of EDO-related news articles collected from the Newsbank database.



(a) Top Negative Words



(b) Top Positive Words

Figure IA2: Distribution of the frequency of top negative and positive words

This figure shows the distribution of the frequency of the top negative and positive words in the sample of EDO-related local news articles, hand-collected from the NewsBank database.

Table IA1: Incidence of delinquency for EDO banks

This table shows the effect of EDOs on auto loan delinquencies. Columns (1) is estimated using an OLS model. The dependent variable is *delinquent*. This analysis utilizes the entropy balanced sample. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The t-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Delinquent
	(1)
Pre EDO	0.011
	(1.289)
During EDO	0.024**
	(2.104)
Post EDO	0.012
	(0.933)
PC Income Growth	-0.010
	(-1.020)
Unemployment Rate	0.347***
	(10.221)
Size	-0.001
	(-0.297)
ROA	0.000
	(0.457)
Liquidity	0.001
	(1.347)
NPA	0.002***
	(2.937)
Capital Ratio	-0.000
	(-0.539)
Observations	1,764,815
Adjusted R^2	0.196
Lender FE	Yes
County × Year-Month FE	Yes
Model	OLS

Table IA2: Local news environment and financial distress

This table shows the effect of EDOs on auto loan delinquencies, differentiating counties by whether they are news deserts and controlling for low income census tracts. Columns (1)–(4) columns are estimated using a lognormal survival (AFT) model. Columns (1)–(2) use average individual income as the interacted control variable and include increasingly stringent control variables and fixed-effect/stratification structures. Columns (3)–(4) use average household income as the interacted control variable and include increasingly stringent control variables and fixed-effect/stratification structures. All standard errors are clustered at the bank level. The dependent variable is *Time to Delinquency*. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency			
	Income: Individual		Income: Household	
	(1)	(2)	(3)	(4)
EDO	0.167	0.165	0.166	0.162
	(0.866)	(0.854)	(0.878)	(0.853)
Pre EDO	-0.062	-0.059	-0.073	-0.070
	(-0.672)	(-0.641)	(-0.789)	(-0.756)
During EDO	-0.332*	-0.327	-0.337*	-0.329*
	(-1.693)	(-1.639)	(-1.751)	(-1.691)
Post EDO	-0.286	-0.292	-0.301	-0.305
	(-1.212)	(-1.199)	(-1.267)	(-1.251)
News Desert	-0.110	-3.216	-0.105	-3.155
	(-1.278)	(-1.606)	(-1.232)	(-1.576)
Low Income	-0.246***	-0.087**	-0.275***	-0.127***
	(-5.798)	(-2.257)	(-7.426)	(-4.082)
EDO × *News Desert*	-0.177	-0.179	-0.164	-0.175
	(-0.748)	(-0.700)	(-0.703)	(-0.698)
Pre EDO × *News Desert*	0.233	0.207	0.214	0.199
	(0.844)	(0.741)	(0.792)	(0.726)
During EDO × *News Desert*	0.661**	0.630**	0.642**	0.625**
	(2.513)	(2.309)	(2.467)	(2.344)
Post EDO × *News Desert*	0.520*	0.473*	0.505*	0.462*
	(1.894)	(1.684)	(1.889)	(1.682)
EDO × *Low Income*	0.044	0.045	0.050	0.053
	(0.337)	(0.351)	(0.408)	(0.437)
Pre EDO × *Low Income*	-0.036	-0.038	-0.011	-0.007
	(-0.341)	(-0.342)	(-0.081)	(-0.050)
During EDO × *Low Income*	0.113	0.123	0.122	0.130
	(1.077)	(1.094)	(1.222)	(1.265)
Post EDO × *Low Income*	0.009	0.026	0.045	0.061
	(0.059)	(0.166)	(0.308)	(0.398)
During EDO + *During EDO* × *News Desert*	0.329	0.304	0.305	0.296
	(1.428)	(1.351)	(1.346)	(1.340)
Observations	46,884,698	45,077,491	46,881,022	45,074,043
Wald χ^2	18167***	18930***	18220***	19147***
Bank controls	Yes	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes	Yes
Additional Economic controls	No	Yes	No	Yes
News Desert × All Economic controls	No	Yes	No	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Strata	State	State	State	State
Model	AFT	AFT	AFT	AFT

Table IA3: Local news environment with propensity score matched sample

This table presents results for the local information environment analysis using propensity score matching. Panel A shows the results of two sample t-test for the propensity score matched news deserts and control counties. Panel B shows the effect of EDOs on auto loan delinquencies using the propensity score matched sample, differentiating counties by whether they are news deserts. Columns (1)–(2) are estimated using a lognormal survival (AFT) model. Column (1) includes year-month fixed effect, and column (2) additionally includes matched-pair fixed effects. All standard errors are clustered at the bank level. The dependent variable is *Time to Delinquency*. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

Panel A: Two-sample t-tests

County Characteristics	News Deserts		Non-News Deserts		t-test	
	N	Mean	N	Mean	Difference	p-value
PC Income Growth	178	0.020	1780	0.018	0.002	0.544
Unemployment Rate	178	0.069	1780	0.069	-0.000	0.986
Population	178	8.894	1780	8.930	-0.036	0.740
PC Income	178	10.135	1780	10.150	-0.017	0.409
Median Age	178	3.681	1780	3.680	-0.012	0.884
Urbanization	178	0.186	1780	0.193	-0.007	0.761

Table IA3: Local news environment with propensity score matched sample, continued

Panel B: Survival models

	Time to Delinquency	
	(1)	(2)
EDO	0.312*	0.265*
	(1.930)	(1.662)
Pre EDO	-0.283***	-0.265***
	(-2.695)	(-2.650)
During EDO	-0.595***	-0.556***
	(-3.522)	(-3.255)
Post EDO	-0.391*	-0.334
	(-1.939)	(-1.618)
News Desert	-0.073	0.043
	(-1.217)	(0.841)
EDO × *News Desert*	-0.049	-0.070
	(-0.213)	(-0.290)
Pre EDO × *News Desert*	-0.022	-0.013
	(-0.116)	(-0.060)
During EDO × *News Desert*	0.487**	0.401*
	(2.370)	(1.855)
Post EDO × *News Desert*	0.198	0.213
	(0.707)	(0.771)
Observations	7,142,080	7,142,080
Bank controls	Yes	Yes
Year-Month FE	Yes	Yes
Matched-Pair FE	No	Yes
Strata	State	State
Model	AFT	AFT

Table IA4: Local newspaper closures and mergers

This table shows the effect of EDOs on auto loan delinquencies, exploiting the staggered closures and mergers of local newspapers across counties. Columns (1)-(3) estimated using a lognormal survival (AFT) model and include increasingly stringent control variables. The dependent variable is *Time to Delinquency*. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency		
	(1)	(2)	(3)
EDO	0.353	0.429**	0.432**
	(1.606)	(1.985)	(1.997)
Pre EDO	-0.037	-0.058	-0.057
	(-0.329)	(-0.565)	(-0.552)
During EDO	-1.059***	-1.085***	-1.085***
	(-7.617)	(-7.527)	(-7.533)
Post EDO	-0.513	-0.593	-0.596
	(-1.417)	(-1.539)	(-1.546)
Post Newspaper Closure	-0.432	-0.526*	2.619
	(-1.521)	(-1.829)	(0.629)
Pre EDO × *Post Newspaper Closure*	0.249	0.241	0.272
	(0.977)	(0.960)	(1.174)
During EDO × *Post Newspaper Closure*	0.915***	0.972***	0.914**
	(3.128)	(3.032)	(2.438)
Post EDO × *Post Newspaper Closure*	0.429	0.635	0.610
	(1.123)	(1.505)	(1.430)
During EDO + *During EDO* × *Post Newspaper Closure*	-0.144	-0.113	-0.171
	(-0.482)	(-0.358)	(-0.470)
Observations	3,157,016	3,016,546	3,016,546
Bank controls	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes
Additional Economic controls	No	Yes	Yes
Post Newspaper Closure × All Economic controls	No	No	Yes
Year-Month FE	Yes	Yes	Yes
Strata	County	County	County
Model	AFT	AFT	AFT

Table IA5: Local news environment: Newspaper publishing establishments

This table presents coefficient estimates from a lognormal survival (AFT) model for changes in auto loan delinquencies by *EDO Cohort*. The variable *Low Establishment Count* is an indicator for a county within the bottom tercile of the number of newspaper publishing establishments. The dependent variable is *Time to Delinquency*. All standard errors are clustered at the bank level. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency	
	(1)	(2)
EDO	0.248	0.236
	(1.361)	(1.292)
Pre EDO	-0.123	-0.110
	(-1.337)	(-1.221)
During EDO	-0.399**	-0.378*
	(-2.035)	(-1.914)
Post EDO	-0.403*	-0.389*
	(-1.804)	(-1.714)
Low Establishment Count	-0.070*	-0.131
	(-1.783)	(-0.188)
EDO × *Low Establishment Count*	-0.249	-0.235
	(-1.189)	(-1.202)
Pre EDO × *Low Establishment Count*	0.159	0.135
	(0.924)	(0.851)
During EDO × *Low Establishment Count*	0.404*	0.386**
	(1.925)	(1.964)
Post EDO × *Low Establishment Count*	0.434**	0.434**
	(2.011)	(2.130)
Observations	45,215,301	43,504,183
Wald χ^2	17338***	19441***
Bank controls	Yes	Yes
Economic controls	Yes	Yes
Additional Economic controls	No	Yes
Low Establishment Count × All Economic controls	No	Yes
Year-Month FE	Yes	Yes
Strata	State	State
Model	AFT	AFT

Table IA6: Borrower sophistication

This table shows the effect of EDOs on auto loan delinquencies, differentiating counties by the average education level of their residents. Columns (1)–(3) are estimated using a lognormal survival (AFT) model. Column (1) uses average high school graduate rate as the cross-sectional variable. Column (2) uses average college graduate rate as the cross-sectional variable. Column (3) uses average postbaccalaureate graduate rate as the cross-sectional variable. All standard errors are clustered at the bank level. The dependent variable is *Time to Delinquency*. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency		
	Education: High School	Education: College	Education: Postbacc.
	(1)	(2)	(3)
EDO	0.182	0.179	0.186
	(1.303)	(1.247)	(1.279)
Pre EDO	-0.053	-0.044	-0.050
	(-0.725)	(-0.615)	(-0.684)
During EDO	-0.236	-0.232	-0.242
	(-1.598)	(-1.489)	(-1.505)
Post EDO	-0.254	-0.243	-0.253
	(-1.414)	(-1.312)	(-1.373)
High Education	0.263***	0.295***	0.270***
	(4.707)	(4.137)	(3.955)
EDO × *High Education*	0.039	0.045	0.024
	(0.314)	(0.356)	(0.233)
Pre EDO × *High Education*	-0.094	-0.146*	-0.128*
	(-1.014)	(-1.826)	(-1.690)
During EDO × *High Education*	-0.219**	-0.270***	-0.225***
	(-2.076)	(-3.015)	(-3.406)
Post EDO × *High Education*	-0.126	-0.197	-0.154
	(-1.013)	(-1.580)	(-1.316)
Observations	46,884,569	46,884,569	46,884,569
Wald χ^2	17348***	17518***	17483***
Bank controls	Yes	Yes	Yes
Economic controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Strata	State	State	State
Model	AFT	AFT	AFT

Table IA7: EDO severity

This table shows the effect of EDOs on auto loan delinquencies, differentiating EDOs based on their severity as proxied by EDO length. Column (1) is estimated using a lognormal survival (AFT) model. All standard errors are clustered at the bank level. The dependent variable is *Time to Delinquency*. All variables are defined in Appendix A. The z-statistics are presented in parentheses; $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ (two-tailed).

	Time to Delinquency
	(1)
Pre EDO	-0.160**
	(-2.366)
During EDO	-0.045
	(-0.549)
Post EDO	-0.103
	(-0.998)
Long EDO	0.871***
	(5.174)
Pre EDO × *Long EDO*	-0.084
	(-0.915)
During EDO × *Long EDO*	-0.551***
	(-4.864)
Post EDO × *Long EDO*	-0.438**
	(-2.270)
Observations	4,105,160
Wald χ^2	117596***
Bank controls	Yes
Economic controls	Yes
Year-Month FE	Yes
Strata	State
Model	AFT