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The Opioid Epidemic and Consumer Credit Supply: Evidence from Credit Cards [*]

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Abstract

Using a unique dataset of unsolicited credit card offer mailings by banks to consumers, we investigate how opioid abuse affects consumer credit supply in the U.S. To identify causal effects, we employ instrumental variables, propensity score matching, and contiguous counties techniques and control for varying local economic conditions and demographics. We find that banks contract credit supply to consumers in counties highly exposed to opioid abuse by offering higher interest rates, lower credit card limits, and fewer rewards and reducing credit offers overall. Further analyses using the supervisory Federal Reserve Y-14M credit card dataset confirm these effects. What is more, the credit contraction disproportionately impacts riskier consumers, minorities (particularly Black people), low-income consumers, and younger individuals. Our examination of various state-level anti-opioid abuse legislation shows that opioid supply-oriented laws are somewhat helpful in curbing opioid overdoses or mitigating the credit supply contraction, but demand-oriented laws are not. Finally, we uncover the real effects associated with the opioid abuse-induced credit contraction: Local consumer spending significantly declines in the highly affected areas, with important macro-policy implications.

JEL Codes: G01, G28, D10, D12, E58
Keywords: Opioid Epidemic, Household Finance, Credit Supply, Spending, Risk

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1 Introduction

During the last two and a half decades, the U.S. has been mired in the opioid epidemic, the longest ongoing health crisis in the country.[1] Since 1999, more than one million people died from overdoses involving either prescription or illicit opioids (Figure 1), surpassing deaths from auto accidents during the same period.[2] Another two million are currently suffering from opioid-related disorders.[3] What is more, the crisis has worsened over time, affecting an increasingly large demographic strata of the population, particularly minorities, young men, and less educated individuals (Figure 2). It is, thus, not surprising that there is now growing evidence linking opioid abuse to reduced labor force participation and increased unemployment.[4]

The adverse effect of the opioid crisis on the labor market has direct implications on consumer finances, as reduction in income is an important determining factor of default. Opioid abusers who use credit to sustain their addiction face additional default risk due to increases in expenditure. This elevated default risk, however, is elusive to lenders because of information asymmetry. Lenders cannot directly detect individuals vulnerable to opioid addiction and/or those who would use the financing to sustain their addiction. As a result, they may shy away from and/or curtail credit in harder-hit opioid areas to reduce exposure.

This paper investigates the effects of the opioid epidemic on consumer credit supply in the credit card market, which is more likely used by the opioid-impacted population as it doesn't require collateral. The credit card market has over 175 million users in the U.S. and spans over 80% of the consumers.[5] Credit cards are also significant determinants of bank risk, partly due to their unsecured nature, inducing high charge-off rates. Sudden and large rises in consumer defaults can deteriorate lenders' portfolio quality and contribute to widespread financial distress

[1]The other health crisis is the recent global COVID-19 outbreak, but its effects were largely mitigated by the quick vaccine development and implementation.

[2]See, among others, Quinones (2015), and the Centers for Disease Control and Prevention (CDC) 2021, https://www.cdc.gov/drugoverdose/deaths/index.html.

[3]https://www.cdc.gov/opioids/basics/epidemic.html.

[4]See Case and Deaton (2015), Van Hasselt, Keyes, Bray and Miller (2015), Krueger (2017), Harris, Kesslery, Murray and Glenn (2019), Park and Powell (2021), Aliprantis, Lee and Schweitzer (2020), and Ouimet, Simintzi and Ye (2020).

[5]See https://www.federalreserve.gov/publications/files/2018-report-economic-well-being-us-households-201905.pdf or https://www.consumerfinance.gov/data-research/research-reports/the-consumer-credit-card-market/.

and crises.

We construct our individual credit supply variables using bank credit card mail offers data from the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File (Mintel/TransUnion Match File). Such credit offers are a direct informative measure of consumer credit supply by the banks, helping circumvent challenges of disentangling supply from demand forces that plague other studies (e.g., Han, Keys and Li (2018)). We focus on the years between 2010 and 2019 so that our results are not contaminated by the implementation of the Credit Card Accountability Responsibility and Disclosure (CARD) Act of 2009, the Great Recession over 2007-2009, or the COVID-19 pandemic from 2020 onward. The years covered in our analyses mark the second and the illicit waves of the opioid epidemic, which recorded perhaps the most dangerous abuse using both prescription and illicit opioids.[6]

To measure the severity of the opioid crisis, we follow the literature reviewed in the next section and construct, at the county level, exposure measures based on confidential opioid-related death rates collected from the CDC/National Center for Health Statistics (NCHS).[7] Consumers' drug abuse is then measured via the severity of the opioid crisis in their county of residence.

Our main findings are as follows. Lenders reduce credit supply significantly in areas with higher exposure to the opioid crisis by charging higher interest rates (1-2 percentage points higher) and offering much smaller credit limits (12%-21% decrease), particularly to consumers with higher perceived credit risk (based on credit score, past delinquency, and derogatory filings, etc.), minorities, low-income consumers, and younger consumers in those areas. Furthermore, banks offer fewer credit card rewards (4% decrease) and are also much less likely (10% decrease) to solicit consumers for credit cards in areas highly exposed to the opioid crisis. Consistent with these credit supply contractions, our analyses of loan performance suggest that lenders decrease credit supply because of increased credit risk in these areas. Specifically, consumers in counties with higher exposure to the opioid crisis experience more days past due and higher probability of default on credit cards, make reduced payments, or have lower credit scores. Additional studies of bank bal-

[6] The first wave involves prescription opioid deaths from the 1990s to 2009; second wave marks the rise in heroin deaths from 2010-2012; and the third wave marks the rise in synthetic opioid deaths, particularly from illicitly manufactured fentanyl.

[7] National Center for Health Statistics, 2020. All-County Mortality Micro Data, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

ance sheets indicate that banks with a significant presence in the more exposed areas experience higher non-performing loans across credit cards and the unsecured consumer sector. We further demonstrate that the reduced credit supply has led to declines in local consumption as captured by credit card purchases. Finally, our analyses of the various state-level anti-opioid regulations targeting both the supply and the demand for opioids reveal that only the supply-oriented laws show some positive effects on curbing the opioid prescription and death rates or reversing the credit contraction in affected areas. The demand/user opioid laws often have reversed or no positive effects.

The identification challenge here and a common concern in the literature is that these negative credit consequences and the opioid exposure may both arise from negative economic conditions that are not observed or controlled for, i.e., the so-called deaths of despair (Ruhm (2019)). To mitigate this concern and isolate the relations studied, we first saturate our models with numerous demand and supply factors by taking advantage of the richness of our datasets. Then, to more formally alleviate the endogeneity concerns and identify causal effects of the opioid crisis, we employ an instrumental variable (IV) methodology by exploiting supply shocks in opioid marketing and distribution. Our approach relies on the observation that prescription opioids are involved in at least 40% of all opioid overdoses in the U.S. (e.g., Hadland, Krieger and Marshall (2017)) and the majority of illegitimate drug users start taking opioids prescribed by their physicians, even if many later progress to illicit opioids (e.g., Kaestner and Engy (2019); Coffin, Rowe, Oman, Sinchek, Santos, Faul, Bagnulo, Mohamed and Vittinghoff (2020)). It is also motivated by the findings in recent economic literature that emphasize the lack of strong correlation between economic activities and opioid abuse (e.g., Ruhm (2019); Currie, Jin and Schnell (2019); Currie and Schwandt (2021); McGranahan, Parker et al. (2021)).

Our main instrument captures the scale of the pharmaceutical industry's opioid marketing to physicians, particularly the number of physicians who receive non-research marketing visits and payments per 1,000 population in a county. This variable is available annually starting in 2013, when the Physician Payments Sunshine Act came into effect. Hadland, Krieger and Marshall (2017) show that pharmaceutical companies invest tens of millions of dollars annually in direct-to-physician marketing of opioids, while Hadland, Rivera-Aguirre, Marshall and Cerda (2019) show that opioid prescriptions and mortality from opioid overdoses went up with the increase in the number of physicians receiving marketing compensation for opioids. This opioid marketing to physicians is unlikely correlated with the consumer or bank credit behavior other than through the increased risks brought on by the opioid abuse itself.

We show that our results are robust to using alternative instruments based on marketing payments made by the pharmaceutical companies to physicians or using the aggressive pre-sample marketing of OxyContin by Purdue Pharma between 1997 and 2002, after its market introduction in 1996. Regarding the latter, Purdue increased its marketing and promotion budget by almost 800% over 1997-2002, marketing the drug aggressively to physicians and pharmacies under the slogan "The One to Start With and the One to Stay With," and turning OxyContin into the most abused prescription opioid by 2004 (e.g., Van Zee (2009); Cornaggia, Hund, Nguyen and Ye (2021)). The growth rates in the locally received OxyContin pills in these early periods were shown to directly impact the rate of opioid prescription by doctors as well as elevated mortality in the later periods, but have little direct correlation with either the financial situation of people or bank lending choices in the affected areas (e.g., Aliprantis, Lee and Schweitzer (2020), Alpert, Evans, Lieber and Powell (2022); Currie and Schwandt (2021)).

We also conduct numerous other robustness analyses to address identification and/or rule out alternative explanations: use alternative definitions for the opioid crisis intensity such as opioid prescription and illicit death rates or use actual opioid prescription rates; employ univariate and regression analyses using propensity score matching where we match the high-quartile opioid deaths counties to other non-treated counties by year and county characteristics using several matching techniques; use contiguous counties to high opioid death counties only; control for even more local market factors; use multiple death causes instead of underlying causes; exclude Florida, which was an epicenter for the opioid crisis distribution; exclude zero-death counties; reconfirm results also using a completely different dataset based on credit card supervisory data; and conduct different cross-sectional tests by consumer characteristics. All of our approaches, despite sometimes covering somewhat different sample periods due to data availability, consistently show statistically as well as economically significant adverse effects on consumer credit risk and credit supply caused by opioid abuse. Additionally, we also uncover evidence that although the opioid crisis had affected the overall population, the negative credit supply effects are larger for riskier consumers; minorities, particularly African Americans; low-income consumers; and younger consumers.

Finally, we analyze the effectiveness of recent laws and regulations about opioid abuse. These laws have been studied only one at a time, making solid policy formulations from them difficult. By contrast, we run a horse race and test six different opioid-related laws at the state level in cross-sectional tests or sample splits. The laws examined can be grouped into two groups, those that target opioid supply, including the Opioid Prescription Limiting Law, the mandatory Prescription Drug Monitoring Program (PDMP) Law, and the Triplicate Prescription Law; and those that affect opioid demand/users, including the Naloxone Law, the Good Samaritan Law, and the Medical Marijuana Permitting Law. We find strong and positive effects of the laws that target opioid supply in reducing opioid prescription and opioid prescription death rates, but limited effects in reducing illicit opioid death rates. Not surprisingly, as a result, we find positive effects from the opioid supply-oriented laws in mitigating credit supply reduction by banks to consumers. In contrast, the laws that target opioid demand, including the Naloxone Law, the Good Samaritan Law, and the Medical Marijuana Permitting Law, have little beneficial or even unfavorable effects on both opioid deaths and consumer credit supply.

The rest of the paper is organized as follows. We discuss the related literature in Section 2. Section 3 presents two simple toy models to illustrate how opioid abuse affects an individual's decision to make loan payments and a lender's decision on loan terms, respectively. The datasets used for our analyses are described in Section 4. Our empirical strategy is described in Section 5. Section 6 presents our results. Section 7 concludes.

2 Literature Review

This paper relates to several strands of literature. First and foremost, there is a large literature in the medical as well as economics field that studies the determinants of opioid abuse. See Currie and Schwandt (2021) and Maclean, Mallatt, Ruhm and Simon (2020) for a review of this literature. The studies generally conclude that neither contemporaneous nor long-term economic conditions can explain a large part of the opioid epidemic. Instead, the opioid spread in the country results from three key factors: a change in beliefs among physicians that pain was not treated adequately; aggressive marketing by pharmaceutical companies that made the claim that the new generation of opioids may have been effective at treating pain with little risk of addiction; and finally, until recently, there was little public oversight of opioid prescriptions by doctors. This literature inspires our choice of instruments as we alluded to in the Introduction.

There also exists a relatively large literature studying the economic impact of the opioid epidemic. For example, several papers find a detrimental impact of opioid abuse on employee productivity and labor market participation (e.g., Van Hasselt, Keyes, Bray and Miller (2015), Krueger (2017); Aliprantis, Lee and Schweitzer (2020); Harris, Kesslery, Murray and Glenn (2019); and Park and Powell (2021)). Focusing on firm outcomes, Ouimet, Simintzi and Ye (2020) find that firm growth is negatively affected by the exposure to opioid-affected areas as the eroding labor market conditions force firms to invest more in technology and substitute capital for the relatively scarcer labor. Rietveld and Patel (2021) and Sumell (2020) find negative impacts on new small firm formation and survival. Finally, Langford (2021) finds that opioid use reduces net firm entry and results in a shift in industrial composition due to labor supply issues in the affected areas, driving long-term stagnation and fiscal difficulties. This literature serves as evidence of the channels through which the opioid crisis affects the consumer markets we study here.

By comparison, only a few papers study the effects of the opioid epidemic on finance. Cornaggia, Hund, Nguyen and Ye (2021) find negative impacts of the local opioid abuse on municipal bonds, which impede municipalities' ability to provide the necessary public services and infrastructure. Custodio, Cvijanovic and Wiedemann (2021) find lower housing values in areas more affected by the opioid epidemic, which are mitigated by the passage of state laws aimed at curbing opioid abuse. D'Lima and Thibodeau (2022) find that house price changes around opioid dispensaries are negatively associated with the quantity of opioids dispensed. Lastly, Jansen (2019) uses data on subprime automotive loans acquired from a U.S. lender and documents an increase in consumer defaults in subprime auto loans as a result of local market opioid abuse problems. We add to this literature by providing the first study of the credit supply consequences of the local opioid abuse along both the extensive margin of credit lending and the intensive margin of credit terms using the credit card market as a laboratory.

3 Simple Models of Opioid Abuse and Consumer Finance

We present two simple models to illustrate how opioid abuse affects an individual's decision to make loan payments and a lender's decision on loan terms, respectively.

3.1 Opioid Abuse and Consumer Loan Repayment Decision

Consider a static model where an individual, after receiving his income and facing necessary consumption such as basic food and rents denoted by c, decides whether to make a loan payment $(1+r)*b$. The term r represents the interest on the loan b. His income is a product of his employment probability e and the wage w he is able to command. If the individual is risk neutral, then the decision is simply captured by his ability to repay,

$$e*w-c-(1+r)*b. \tag{1}$$

The individual will make the payment only if the term in equation (1) is non-negative. Let ϕ denote the repayment decision, then we have $\phi=1$, if $e*w-c \geq (1+r)b$, and $\phi=0$ otherwise.[8]

For a highly dependent opioid user, the drug cost increases his necessary consumption c. Moreover, according to Bickel, Athamneh, Snider, Craft, DeHart, Kaplan and Basso (2020), the addiction itself can lead to other unsound decisions due to a "reinforcer pathology" that increases the individuals' overvaluation of short-term tangible rewards and undervaluation of long-term negative consequences, in addition to impulsivity, nonconformity to rules, and cognitive issues. All these make him less employable and reduce the wages he can command (see the literature review), i.e., both e and w are likely smaller. Last, as we discuss next in lenders' decisions, the person may also face higher interest rate r. If the person is not addicted to opioids but lives in an area heavily exposed to the epidemic, drug cost is no longer an issue, but he may still receive a lower income and be charged a higher interest rate because of the spillover effect due to the information problem employers and lenders face (see our discussion in the next subsection).

All of these factors suggest that a person in an area heavily exposed to opioids is more at

[8] For simplicity here, we rule out partial loan payment cases.

risk of defaulting on his loan obligations and thus a potentially ”riskier” credit borrower. The one countering force in our simple model is if the person also borrows less voluntarily or due to credit rationing, that is, b is smaller.[9]

When we aggregate individual behavior to, for example, the county level, the discussion above suggests that the areas with high-opioid exposure will likely have more consumers default on their loan obligations. An immediate implication is that banks with higher operational exposure to these areas will have riskier consumer loan portfolios, as reflected in a larger share of non-performing loans.

3.2 Opioid Abuse and Consumer Credit Lending Decision

A lender decides how much b to lend and what interest rate r to charge, and his payoff is as follows,

$$\phi * (1 + r) * b - (1 + r_d) * b, \tag{2}$$

assuming that the per-unit cost of funding is r_d and the loan is noncollateralized. If the lender observes the repayment probabilities ϕ, then, in a competitive environment/under a zero profit condition, he sets the interest rate $r = (1 + r_d)/\phi - 1$, which decreases with ϕ.

The biggest challenge posed by the opioid abuse to a lender is information asymmetry. The lender will have to make inferences based on public data such as aggregate opioid-related drug overdoses. Consider two individuals living in areas with different exposures to the opioid abuse crisis, which, in our setup, can be captured by their repayment probability ϕ_1 and ϕ_2, and $\phi_1 < \phi_2$. Everything else the same and absent of other signals, the lender will approximate each individual's repayment probability with the average payment probability of the area that he resides in. It then follows that individual 1 will be charged a higher interest rate than individual 2 despite that the two look similar in all other aspects.

The discussion so far illustrates why lenders would charge individuals in high opioid exposure areas higher interest rates for a given loan amount. Turning to the lenders' loan making

[9] In dynamic models where consumers may need to borrow in many periods and lenders can impose punishment on those who default, drug addicts, having large discount factor, will also be less affected by the punishment.

decision, according to Stiglitz and Weiss (1981), credit rationing can arise under certain conditions with information asymmetry. For example, consider an environment where individuals have different probability distributions of income y, and different addiction or exposure to opioids captured by θ, $F(y, \theta)$, and they need to borrow a fixed amount b. Additionally, there is a fixed cost d associated with each defaulted loan for the lender. This problem maps into that in Stiglitz and Weiss (1981) (see *Alternative Sufficient Conditions for Credit Rationing*, p. 399), where the expected revenue for lenders as a function of the interest rate charged will be hump shaped due to information asymmetry under the condition that a small change/rise in interest rate induces a large change/worsening in applicant pool. As a result, lenders will not lend if the perceived opioid exposure exceeds a certain threshold. In other words, credit rationing arises in those cases.

To summarize, our discussions indicate that individuals in the high exposure areas are at higher risk of default, that banks operating in those areas have riskier consumer loan portfolios, and that lenders are likely to lend less to them if at all and/or charge them higher interest rates. These are the hypotheses that we will test in the next sections.

4 Data Sources and Data Collection

We make use of several types of data: information on opioid crisis intensity and marketing practices; financial information on consumer credit supply, and local economic and demographic information. Data measuring opioid crisis intensity and marketing practices are at the county by year level. Data measuring credit offers are at the individual/offer by year-month level. In additional analyses testing potential underlying channels for our main results, we also use data on consumer loan performance and bank loan portfolio risk. Data measuring credit performance are by county by year-month (or county by year-month) level. Data measuring bank outcomes are at the bank by year-quarter level.

4.1 Opioid Mortality and Marketing Practices

4.1.1 Opioid Mortality Rates

We obtain restricted-use mortality data from the CDC (the All-County Mortality Micro Data; NCHS, 2020). These data provide the precise cause of every death in every county and hence allow us to accurately identify all opioid-related deaths by location. From these data, we construct the number of opioid-related deaths scaled by the county's population (in 10K) in each year. In some additional analyses, we also differentiate between prescription- and illicit-drugs-related deaths. Prescription-deaths capture the illegal diversion of legally manufactured prescription opioids for non-medical use and unfortunate externalities of medical use of the prescription opioids, while illicit deaths are related to the use of "street drugs," such as heroin or illicitly manufactured fentanyl.[10] A high opioid mortality rate is indicative of a high addiction rate, and public officials also rely on such mortality rates as one of the best metrics to monitor the opioid crisis across regions.[11]

We focus on opioid mortality as our primary measure of opioid abuse. In addition to being comprehensive and comparable across counties, this measurement, in comparison to opioid prescription rates often used in the literature, better captures the progression in the opioid epidemic since 2010, the period of our analyses, that is, the rise in illicit opioid drug abuse.

We supplement the mortality opioid data with opioid prescriptions in some additional analyses. We use the opioid prescribing rates per capita, per county each year derived from the CDC public data.[12] The CDC's prescribing data originate in the IQVIA Transactional Data Warehouse (TDW), which is based on a sample of approximately 59,000 non-hospital retail pharmacies. These pharmacies dispense about 90% of all retail prescriptions in the country. Several prior studies find

[10] To construct opioid-related deaths, we follow Cornaggia, Hund, Nguyen and Ye (2021) (Appendix A.1) by identifying drug-related deaths first, i.e., those with underlying ICD-10 cause codes X40-X44 (accidental poisoning), X60-X64 (intentional poisoning), X85 (homicide), and Y10-Y14 (undetermined intent). We then narrow to causes related to opioids, i.e., those with a contributing cause code of T40.0 (opium), T40.1 (heroin), T40.2-T40.3 (prescription), and T40.4 (synthetic opioids, primarily fentanyl). Finally, we use the multiple cause portion of the death certificate and assign to Illicit category all deaths that have opium (T40.0), heroin (T40.1), and synthetic opioids (T40.4) causes and assign the rest (T40.2–T40.3) to the prescription category.

[11] The death data used here are superior to the public CDC data on opioid deaths, as the public data omit counties with fewer than 10 drug-poisoning deaths, thus leaving out nearly half the population. This left-tail censoring also creates time series problems as some counties were reported in some years but not others.

[12] See https://www.cdc.gov/drugoverdose/maps/rxrate-maps.html.

that opioid prescriptions are a good proxy for opioid addiction and abuse and/or find a positive correlation between rates of prescriptions and subsequent abuse in an area (e.g., Schnell (2019); Ouimet, Simintzi and Ye (2020)).

4.1.2 Opioid Distribution and Marketing

We construct the main opioid marketing instrument based on the non-research transfer marketing information from the pharmaceutical industry to physicians following Hadland, Rivera-Aguirre, Marshall and Cerda (2019). Specifically, we collect data on the number of physicians being marketed opioids by their practice county and by year from 2013 onward from the Centers for Medicare and Medicaid Services Open Payments database.[13]

We check the robustness of our main results to using alternative instrumental variables. Thus, we construct another instrument based on non-research transfer marketing information payments from the pharmaceutical industry to physicians again following Hadland, Rivera-Aguirre, Marshall and Cerda (2019). Lastly, we also construct an opioid marketing instrument based on the aggressiveness of Purdue Pharma's marketing of OxyContin in the pre-crisis era. We hand collect data on all Oxycodone pills distributed to each zip code each year from archived Drug Enforcement Administration (DEA) reports. We then aggregate the data to the county level and compute the county growth rate of Oxycodone pills distributed between 1997 (the year after OxyContin was introduced) and 2002.

4.2 Consumer Credit Supply and Other Consumer Finance Information

4.2.1 Consumer Credit Supply

For credit supply, we use the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File (Mintel/TransUnion Match File) proprietary survey of U.S. consumers merged with TransUnion consumer credit bureau characteristics over 2010 to 2019, which was also de-personalized after the merging process. Each month, Mintel selects about 4,000 consumers from a pool of one million consumers that Mintel acquired from a large survey ser-

[13] Centers for Medicare & Medicaid Services. Open Payments dataset, https://www.cms.gov/openpayments/explore-the-data/dataset-downloads.html, accessed March 12 2022. The database is mandated by the Physician Payments Sunshine Act.

vice provider. Mintel gives each consumer a set of envelopes and asks the consumer to put mail from an array of sectors, including credit offers, into the envelopes and send them back to Mintel weekly during the participating month. Once receiving the envelopes, Mintel records almost all information from the credit offers, whether a consumer receives an offer, and credit terms of the contracts offered, such as interest rates and credit limits.

The Mintel credit offers monthly data were merged with credit bureau information on the consumers from TransUnion and subsequently anonymized to protect the confidentiality of the survey participants. The combined data are the Mintel/TransUnion Match file that we use in our analysis.[14] We focus on credit card offers, which have the best data coverage, and ”banks” that are filtered using lender names containing keywords such as “bank,” “bancorp,” “banco,” etc. We keep in our analysis only those credit offers that have non-missing APR purchase rates and limits for the offers, as well as non-missing consumer characteristics. The consumer credit score and score ranges used in this analysis are from the Mintel/TransUnion Match file.

4.2.2 Other Supplementary Data

Consumer Credit Performance For consumer credit quality/performance, we use the Federal Reserve FR Y-14M regulatory report, collected by the Board of Governors of the Federal Reserve System in pursuance of the annual comprehensive capital analysis and review (CCAR) of large U.S. bank holding companies, as required by the 2010 Dodd-Frank Wall Street Reform and Consumer Protection Act. The monthly report for each account originated and managed by the reporting banks contains detailed information on borrower characteristics, credit card days past due, loan probability of default (PD), payments, terms, and also purchases. This credit card dataset is very large, more than 500 million observations per month. We therefore follow common practice in the literature and employ a 0.1% random loan-level sample for existing credit card accounts (having been in existence for at least 12 months) that are nationally representative across U.S. states as well as across banks' portfolios. We work with existing accounts because we want to observe their credit behavior and quality as well as their spending patterns.

The banks in the FR Y-14M report dataset are dominant players in the credit cards market,

[14] The merge is conducted by the vendor for the anonymized file, and we only work with the anonymized file.

holding a combined market share of over 75% as of December 2019, so the accounts are likely representative of the market as a whole.[15] To remove reporting errors, we exclude from our sample loans that are subject to SOP 03-03 accounting (i.e., it is purchased credit-impaired loan or a purchased loan with evidence of deteriorating credit quality since origination); loans with erroneous credit scores (credit scores are missing or outside the range of 300 to 900); loans with missing or credit limit or APR; and accounts that are deactivated and/or inactive.

Bank-Level Consumer Portfolio Data The quarterly regulatory Consolidated Reports of Condition and Income, generally referred to as the Call Reports, help extend our study to bank level. Call Reports are provided by the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution. Every national bank, state member bank, and insured nonmember bank is required by the FFIEC to file a Call Report as of the close of business on the last day of each calendar quarter, i.e., the report date. Call Reports provide information on the institution's balance sheet, income statement, and a narrative explaining elements of the financial statements. We focus on nonperforming loans ratios for credit cards and the unsecured consumer segment.

County-Level Expenditure and Other Economic Data We proxy county level consumption by aggregating domestic credit card purchases provided by the FR Y-14M data discussed above to the bank level by county and by year-month. We obtain similar results using data aggregated at the county by year-month level.

Additionally, we obtain average income from the Bureau of Economic Analysis (BEA), unemployment rate from Bureau of Labor Statistics (BLS), and bank competition in the county measured by the Herfindahl-Hirschman Index (HHI) of deposits based on the FDIC Summary of Deposits data. We obtain additional county demographic information such as population by race, gender, age, educational attainment, and inequality from the U.S. Census Bureau American Community Surveys.

[15] This is based on market share assessments of these banks' balances in the FR Y-14M compared to the credit card balances in the Federal Reserve Bank of New York Quarterly Report on Household Debt and Credit as of 2019:Q4 available at https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data.

5 Estimation Strategy

We do not observe directly consumers' opioid usage and health status and, therefore, cannot directly test the impact of the opioid usage on credit supply. Instead, we test whether banks are less likely to supply credit or apply more stringent terms to individuals in more opioid-affected areas. We measure a county's exposure to the opioid crisis by its opioid death rates. For each credit supply variable, we test whether opioid exposure has any explanatory power in addition to the control variables. The exposure measures are lagged by one year.

Estimating the effects of the opioid crisis on consumers and banks raises endogeneity concerns as common conditions or shocks may drive both the opioid crisis intensity and the credit outcomes. To attenuate these concerns and ensure we identify the causal relationship between opioid epidemic exposure and various consumer credit consequences, we conduct two-stage least square (2SLS) regression analyses that use instrumental variables for the opioid crisis intensity.

Additionally, we introduce an extensive set of control variables that capture heterogeneity in county, consumer, and bank characteristics as relevant in different parts of our analyses. We note that all our controls in all analyses are lagged one period (one year, one quarter, or several months, based the data availability). At the county level, we control for indicators of local economic conditions, including median income, income inequality (Gini index), and unemployment rate, as well as a variety of demographic characteristics such as population density, race, gender, age, and educational attainment composition. We also control for banks' local market concentration (HHI of deposits), to account for potential uneven access to banking services and credit terms. Finally, we include combinations of state, bank, and time fixed effects, pertinent to each dataset and analysis, to further account for unobserved characteristics.

5.1 Instrumental Variable First-Stage Specification

In the first stage across all our analyses, we regress the opioid crisis exposure variable on the instrument and the same set of controls as those included in the second stage for the corresponding analysis, which we specify in detail below. The general first-stage specification is as follows:

$$\begin{aligned}OpioidExp_{c,t-1} = \gamma_0 + \gamma_1 IV_{c,t-1} + \gamma_2 CountyControls_{s,t-1} + \gamma_3 OtherFE \\ + \gamma_4 OtherConsumer/BankControls_{i,c,t-1} + \mu_{c,t-1},\end{aligned} \tag{3}$$

where i indicates individual or bank, c county, and t time.

As discussed in Section 4.1.2, the main instrumental variable (IV) we use is *MKTDoctors/1000Pop*, the number of doctors receiving opioid marketing payments from pharmaceutical companies per 1,000 population per year in the main analyses, which is time variant, covering 2013 onward. In robustness tests, we also use as additional IV, *MKTPayments/1000Pop*, the number of non-research marketing payments made to doctors by pharmaceutical companies per 1,000 population per year, also time variant. Finally, we also use as an alternative IV, *Purdue MKT (OxyContin Growth '97-'02)*, the growth rate in each county in the distribution of OxyContin pills between 1997 and 2002 for robustness test, which is time invariant.

5.2 Second-Stage Specifications

We next discuss the econometric models for the IV second stage credit outcome analyses. We use $\widehat{OpioidExp}_{c,t-1}$ to denote the predicted value of $OpioidExp_{c,t-1}$ obtained from the first stage.

5.2.1 Consumer Credit Supply

The credit supply Mintel/TransUnion Match file data are at the credit offer by year-month level. Our outcome variables are the bank's willingness to lend to different categories of consumers reflected in the likelihood of unsolicited credit card offers, as well as the credit terms applied to those offers captured by $Y_{i,c,t}$ for consumer i in local market (county) c at time (year-month) t:

$$Y_{i,c,t} = \delta_0 + \delta_1 \widehat{OpioidExp}_{c,t-1} + \delta_2 ConsumerControls_{i,t-1} + \delta_3 CountyControls_{c,t-1} + FE + \xi_{i,c,t}, \tag{4}$$

where $Y_{i,c,t}$ refers to one of the main credit card offer terms such as the $RateSpread$, the difference between the offered credit card APR and one-month Treasury bill, or $Ln(Limit)$, the natural log of the offered credit card limit. In additional analyses, we also analyze *Reward/Promotion*, a binary indicating whether a credit card offer includes rewards and/or promotions, and *Card Offer*, a binary indicating a consumer is receiving a credit card offer in a particular month or not.

Consumer-level controls (measured as of 2-3 months prior to the credit offer) include credit scores ranges, consumer income, binaries for recent delinquency (90 days or more past due) on any of the credits held, other derogatory information such as foreclosures, past bankruptcy filings, previous other credit cards, previous high credit card utilization (80% or higher), as well as the natural log of the number of recent credit inquiries (proxying for consumer credit demand). We also include age range binaries to account for potential nonlinearity in credit supply, indicators for homeowner, married, no children, education level, and indicators for non-minority or White consumers. Finally, we include all additional county-level controls as discussed above (lagged one period).

We also include a battery of fixed effects including lender by year-month, state by year-month, lender by state, as well as lender, state, and year-month fixed effects, whenever possible, to capture lender health and business models and practices over time, local market changes over time, bank strategies across states, as well as unobserved factors at the lender, state, or year-month levels. Standard errors are double-clustered at the marketing campaign and year-month level. [16,17]

5.2.2 Other Consumer Finance Outcomes

Consumer Credit Performance For consumer credit performance, we use the FR Y-14M data, where the unit of observation is county by year month. The outcome variables are average days past due, probability of default, average payment, and average consumer credit score.

Our estimation specification of consumer credit performance for local market (county) c at time t is as follows:

$$Y_{c,t} = \beta_0 + \beta_1 \widehat{OpioidExp}_{c,t-1} + \beta_2 CountyControls_{c,t-1} + FE + \epsilon_{i,c,t}, \quad (5)$$

[16] Note that we are able to include lender by year-month fixed effects for all our credit card terms analyses, as all credit offers are associated with a lender, but not for the regressions looking at the likelihood of getting a credit card offer, as not all consumers get an offer from a lender.

[17] A unique strength of the Mintel/TranUnion Match data is that they report all consumers and their characteristics regardless of whether they received a credit card offer in a particular month, allowing us to study the credit supply at the extensive margin in addition to the intensive margin based on credit card terms for those who did receive an offer.

where $Y_{c,t}$ is one of the outcome variables. We include the same county by year information (also lagged one period) as those in the credit supply analyses.

Bank-Level Consumer Portfolio Risk For bank-level consumer credit risk, we use the regulatory Call Reports data, where the unit of observation is bank by year-quarter. The opioid crisis variables and the instruments here are weighted averages of a bank's exposure to the opioid death rates or opioid marketing practices, across all counties in which the bank operates, using proportion of bank branches in the county as weights.[18] The first stage is modeled as per equation (3) above. The outcome variables here are the bank's non-performing loans for credit card debt or other unsecured consumer loans relative to bank total assets. Specifically, our estimation specification of bank consumer loan portfolio performance for a bank j at time (year-quarter) t follows:

$$Y_{i,t} = \psi_0 + \psi_1 \widehat{OpioidExp}_{i,t-1} + \psi_2 BankControls_{i,t-1} + \psi_3 CountyControls_{c,t-1} \psi_4 FE + \zeta_{i,t}, \quad (6)$$

where $Y_{i,t}$ refers to proxies of bank portfolio performance. Controls for bank characteristics (lagged one period) include tier 1 capital ratio, liquidity ratio, bank profitability, the log of bank total assets, and bank age. We also include bank exposure to various economic and demographic county conditions other than the opioid crisis as those used in the credit supply analyses but aggregated to the bank level, based on the bank's branch share in each county of operation.

5.2.3 County Consumption

For local consumption, we aggregate the Y-14M domestic credit card purchases by county year-month. Let $Y_{c,t}$ denote the log of consumption for county c at time t, the estimation equation is as follows,

$$Y_{c,t} = \theta_0 + \theta_1 \widehat{OpioidExp}_{c,t-1} + \theta_2 CountyControls_{c,t-1} + FE + \eta_{c,t}, \quad (7)$$

where the county level controls are the same as those used in the credit supply specification.

[18]Branch deposit data are sourced from the FDIC Summary of Deposits.

6 Empirical Results

6.1 Opioid Abuse Intensity over Time and Space

As discussed earlier, we measure opioid abuse intensity at the county level by opioid-related death rates per 10k county population. Figure 1 presents the evolution of opioid-related overall deaths and when split by prescription and illicit drugs over time. The figure captures the two important waves in the crisis: the heroin (mostly illicit) overdose wave from 2010 to 2012; and the synthetic (illicitly manufactured) opioid overdose wave from 2013 onward.

As Figure 1 demonstrates, the overall opioid death rates have been moving up consistently over our sample period, driven by rises in the illicit death rates. By comparison, the prescription death rates remain stable at relatively low levels, likely due to the decline in opioid prescription rates starting in 2012 resulting from policies aimed at reducing opioid abuse.[19] As noted by prior research, many of the initial users of prescribed opioids progressed to illicit or illegal opioid use. Later, the availability of relatively cheap and easy to produce street drugs such as fentanyl further fueled the surge in illicit opioid use. As a result, the overall opioid deaths accelerated rapidly from 2013 onward, just as illicit opioid deaths started to register high growth.

Figure 2 illustrates changes in consumer demographics in opioid-related deaths over time. Overall, the opioid crisis appears to be widespread among all races, age groups, genders, and people of various education levels. However, we note a few shifts in these demographics over time. First, while we continue to see a rise in opioid death rates among White people, the rises in death rates are more significant among minorities, particularly Black people, whose opioid-related death rates surpassed White deaths in 2020. Second, while all age groups are affected, there is clearly a higher proportion of working age people, and this proportion is consistently increasing over time. Third, both men and women die from overdoses, but men are disproportionately more affected, and the gap between genders only increases more in the last illicit wave. Lastly, among people of various educational attainment who die from opioids, we observe a higher percentage

[19] The Prescription Drug Monitoring Programs (PDMPs) are examples of such policies operated by states and established to collect opioid prescription data and facilitate the sharing of these data between providers and authorities, in an attempt to reduce opioid abuses (e.g., Buchmueller and Carey (2018)). We investigate the effects of the opioid-related laws in later sections.

of deaths among people with lower levels of education (high school or less) and this gap widens significantly in the last illicit wave. We will exploit these heterogeneities in some of our later credit supply analyses to understand whether certain demographic groups are treated differently than others.

Figures 3 provides the geographical distribution of opioid-related death rates using the confidential CDC mortality data across counties in 2019. The darker red indicates areas with higher deaths or prescription rates. We observe stark regional variation in crisis intensity: areas in the middle and north of the country are less affected than areas in the west and the south.

6.2 Opioid Crisis and Marketing/Medical Practices: The Instrument

The construction of our instruments reflects the argument that the geographic differences in opioid abuse are closely related to the differing medical practice of doctors, as well as the differing marketing practices of pharmaceutical companies. Deteriorating economic conditions, by contrast, are not a significant driver for these differences.[20]

Formally, in order for our instrument of local opioid marketing/medical practices to be valid, they must be correlated with opioid abuse intensity. Figure 4 plots the average *MKT Doctors/1000Pop*, the number of doctors in the county who received marketing visits and payments (from pharmaceutical companies) for opioids per 1,000 county population, over 2013-2019. Figure 5 presents binned scatter plots of our opioid intensity measures, *Opioid Death Rate*, against the instrument after controlling for year and state fixed effects.

Overall, the opioid measures show a positive correlation with our instrument, as evidenced by both the geographical distribution as well as the scatter plot, which is striking but not surprising. According to Hadland, Krieger and Marshall (2017) and Hadland, Cerdá, Li, Krieger and Marshall (2018), between 2013 and 2015, approximately 1 in 12 U.S. physicians received opioid-related marketing visits and payments; this proportion was even higher for family physicians, among whom 1 in 5 received opioid-related marketing support. Marketing strategies of the pharmaceutical companies include visits and direct payments to the doctors as well as more intense

[20] See Maclean, Mallatt, Ruhm and Simon (2020), Ouimet, Simintzi and Ye (2020), Currie and Schwandt (2021), and papers cited therein for detailed discussion.

early distribution.

Furthermore, Table 2 Panel A for credit supply below more formally discusses the first-stage estimation results for credit supply using Mintel/TransUnion Match File analyses. Those analyses document a significant positive association between our measures of opioid abuse intensity and the instrument, after controlling for a wide range of consumer and county characteristics as well as location and time fixed effects. Moreover, the weak identification and underidentification tests suggest that the instrument is relevant and valid.

Having established that our instrument satisfies the relevancy requirement, we now turn to discussing whether it also satisfies the exclusion requirement. There are reasons to believe that marketing of opioids should not have a direct causal effect on consumer financial outcomes other than through its influence on the opioid prescriptions and deaths. Neither consumers nor banks have any control over the opioid marketing in their area, nor is it reasonable to assume that they would relocate just to be in an area with more aggressive opioid marketing. Further, marketing of opioids alone, if it does not lead to any changes in opioid prescriptions and deaths, is unlikely to affect in any way consumer credit outcomes. Finally, as mentioned in the Introduction, several studies in prior literature show that demand-side factors alone, such as physical pain, depression despair, and social isolation due to poor economies can explain only a small fraction of the increase in opioid use and deaths. Moreover, despite the fact that some economic changes over the past few decades may be related in some cases to opioid overdose deaths, such an impact on the rise in overall opioid use remains modest.[21] We confirm in Table 1 Panel B that there exists little correlation between our instrument, *MKT Doctors/1000Pop*, and various key economic and other county characteristics, including income, unemployment rates, labor force participation rates, house price indices, average credit score, and poverty rates.

[21] See, among many others, Cutler and Glaeser (2021), Alpert, Evans, Lieber and Powell (2022), and papers reviewed in Maclean, Mallatt, Ruhm and Simon (2020).

6.3 Main Results

6.3.1 Consumer Credit Supply

According to our theory, banks reduce their credit card supply to consumers in counties with high opioid crisis intensity. We test this hypothesis by examining both bank credit card offers terms, credit supply at intensive margin, and the likelihood of a consumer receiving credit card offers, credit supply at extensive margin. We use the Mintel/TransUnion Match File, which includes direct measures of bank credit supply as banks send unsolicited offers to the prospective credit card consumers.

Table 1 Panel A presents summary statistics for the key variables used in this part of the analyses. We note that consumers in the study have relatively sound financial profiles, with a mean credit score of 703, and an average income of $\$57,411$. In other details, we find that 21% of the consumers have had at least one 90+ days past due delinquency on any credit product, 7% have filed for bankruptcy in the past, and 2% have had credit card utilization rate at 80% or higher in the past. Demographically, the average consumer is 50 years old, 75% of consumers are homeowners, 31% are married, and 41% have no children. During the period of our study, county overall opioid death averaged 1.2 per 10,000 population while illicit opioid deaths averaged 0.86 per 10,000 population. The opioid prescription rates average 0.72 per capita.

Tables 2 report the IV 2SLS regression estimates for the effects of the opioid crisis on consumer credit card terms, where Panel A shows the first-stage IV results, and Panel B shows the second-stage IV estimates, when using *MKTDoctors/1000Pop* instrument. As above, for brevity, we include only the coefficients of interest. The key dependent variables are either *Rate Spread*, the APR credit card spread, or *Limit* expressed as either (*Ln(Limit)*), the natural log of the offered credit card limit or (*Limit($)*), the actual limit in dollar value. The main independent variables are the two opioid intensity measures both lagged 1 year, corresponding to continuous opioid deaths rates or indicators for high opioid in the top half of the distribution (50th percentile and above) in different specifications. As discussed in Section 5, we control for consumer credit quality in many ways, including credit score ranges, income, past delinquency, past derogatory filings, past bankruptcy filings, past high credit utilization, as well as for credit demand based on consumer credit inquiries and other personal characteristics as of two-to-three months prior to the credit offer. We also control for a rich set of economic and demographic county characteristics, plus numerous fixed effects to isolate as well as possible the effects studied. Thus, we include: Lender × Year-Month, State x Year-Month, Lender x State, Lender, State, and Year-Month fixed effects, to absorb variation in lender and state conditions over time, or lender over state as well as to account for other unobserved factors at the lender, state, or time levels.

In all cases, the IV first-stage estimates indicate that our instruments are significantly positively associated with higher opioid crisis intensity, while the IV first-stage statistics show that instruments are relevant and valid.[22] The IV second-stage estimates further show that accounting for a very rich set of supply and demand factors, consumers residing in counties more affected by opioid abuse experience significantly lower credit supply at the intensive margin.[23] These consumers are offered higher credit card APR spreads and lower credit card limits. For instance, individuals living in counties with opioid death rates in the nation's top half of the distribution (50th percentile and above) receive, on average, a credit card interest rate that is 1.2 percentage points higher, and a credit limit that is $194 lower. These numbers are economically significant, as they amount to a 7 percent (= 1.2/17) increase in interest rate and a 21 percent (= 194/941) reduction in credit limit for an average borrower.

6.3.1.1 Using Alternative Opioid Death Measures

Given the changes over time in drugs responsible for opioid deaths, with illicit drugs becoming more prominent in recent years than prescription drugs, Table 3 reiterates our main results for credit supply terms for consumers when looking separately at rates of prescription and illicit opioid deaths. Panel A reports the first-stage results where we show that the instrument continues to work well for both measures. Panel B reports IV second-stage results when using *MKT-Doctors/1000Pop* as an instrument for opioid abuse intensity. We find significant increases in credit card spreads and lower credit card limits from both types of death rates; however, magnitudes and

[22] We check the first-stage statistics in all our IV 2SLS analyses that we use in this paper, and all are in line with expectations. For brevity, we do not report these in all tables, but they are available from the authors upon request.

[23] Appendix Table A2 Panel C reaches similar conclusions using OLS estimations.

significance are much larger for the illicit opioid deaths when measured as whether the county is in the nation's top half of the distribution (50th percentile and above) or not.

6.3.1.2 Using Opioid Prescription Rate

An alternative measure of opioid exposure that has been used in the literature is opioid prescription rate, which played an important role prior to 2014, i.e., during the first and the second waves of the opioid crisis. In Table 4, we repeat our analysis using county opioid prescription rates, either continuous or as an indicator of whether it exceeds the nation's median rate. As indicated in Panel B, we see a statistically significant and economically important negative effect on credit supply, though the effects are somewhat smaller than our benchmark estimates.

6.3.1.3 Using Different Instruments

We next repeat our benchmark analyses using two alternative instruments: the marketing payments per 100 county population and the growth rates in each county in the distribution of OxyContin pills between 1997 and 2002.

We report the second-stage results in Table 5 Panel A and Panel B, respectively. Again, we continue to see opioid abuses having a large and significant effect on local credit supply and the effects are particularly large in magnitude when we use the second instrument, the growth rates of the distribution of OxyContin pills between 1997 and 2002.

6.3.1.4 Alternative Identification Strategies

A potential concern with our benchmark analyses is that our results could be prone to self-selection bias if consumers are not randomly assigned across counties, and the opioid crisis determinants at the county level may affect credit terms. To help dispel the competing explanation that our results may spuriously reflect differences in the characteristics of high- and low-opioid crisis counties rather than the opioid crisis intensity per se, we conduct several additional analyses.

First, we conduct a univariate analysis based on several propensity score matching (PSM) techniques in Table 6 Panel A. We match counties in the 25th percentile of the distribution each year in terms of opioid intensity with other counties similar in terms of economic and demographic characteristics as used in our main analysis based on predicted propensity scores. We use several matching techniques, including one-to-one matching without replacement, matching each treated county (high opioid group) to the nearest untreated (control, low opioid group) county each year. This technique ensures we do not have multiple control counties assigned to the same treated one, which can lead to a smaller control group than the treated group. We also use one-to-one matching with replacement, which differs in that each treated county is matched to the nearest control county even if the latter is used more than once. Additionally, we use nearest-neighbor matching with n=2, n=3, and n=5 with replacement, which matches each high opioid county with the two, three, or five low opioid counties with the closest propensity scores, respectively. We then calculate the opioid crisis effect on credit card terms as the mean difference between high-opioid counties' terms and those of their matched low-opioid peers. All differences are significant at the 1% level and show significantly harsher credit card terms in high-opioid counties relative to the control group.

Second, we use IV 2SLS regression analysis based on constrained samples comprising counties in the top 25th percentile of the distribution each year in terms of opioid intensity with other low opioid death counties similar in characteristics using one-to-one matching without and with replacement and report results in Table 6 Panels B and C.

Finally, in another approach as reported in Table 6 Panel D, we match high opioid counties in the top 25th percentile of the distribution with their neighboring counties that are in the low opioid remaining group and again run IV 2SLS regressions analysis using this constrained sample. Neighboring counties are assumed to have very similar economic and other conditions, making the two groups more comparable. Despite the significant loss in the number of observations, in all these additional regression analyses, we continue to find significantly harsher credit card terms (higher rate spread and lower limits) for consumers in highly affected opioid counties.

6.3.1.5 Other Robustness Tests

We conduct additional robustness tests and report the results in the Appendix Table A2. First, we add even more county-level controls, including county labor force participation rate, average credit score, air pollution, house price growth rate, percent of school dropouts, the percentage of a county's population claiming affiliation with an organized religion, and the relative strength of the Democratic/Republican party as captured by county election/voting outcomes, poverty rate, as well as percent of population in poor health (Panel A). Next, we use alternative opioid death rates based on multiple death causes instead of single deah causes as in the benchmark (Panel B). We also conduct simple OLS regressions (Panel C); exclude counties with zero opioid-related deaths (Panel D); and, finally, we exclude Florida from the analysis, as Florida was an epicenter for the opioid drug distribution. In all of these analyses, we continue to find significantly adverse effects on consumer credit supply from opioid epidemic exposure both in credit card interest rates as well as the credit card limits offered by banks.

6.4 Consumer Heterogeneity Tests

Higher-risk borrowers can be more easily affected by external shocks, and we conjecture that banks may exercise extraordinary caution toward the more vulnerable categories of consumers in highly opioid-affected areas. Moreover, our earlier Figure 2 about the evolution of the crisis by demographics showed stark and disproportionately higher opioid death rates in the recent illicit opioid waves for people with less education (important to note because education tends to be highly correlated with consumer income and credit score); minorities, particularly Black people; males; and younger and/or working-age people. The richness of our credit supply data allows us to test whether our main findings may differ across these characteristics. Specifically, we analyze interactions between the opioid crisis intensity and consumer high credit risk indicators, while continuing to use *MKTDoctors/1000Pop* as an instrument for opioid abuse intensity. Results from the IV 2SLS second stage are reported in Tables 7 and 8. The consumer risk metrics utilized are indicators for *Subprime* (credit score below 620) and past deep delinquency (90 days past due). We also additionally conduct tests for differential impacts on minorities, low income (<30K), and younger consumers ($<$ 25 years old).

We consistently observe that banks apply additionally harsher credit card terms for riskier consumers, as proxied by their credit score and past delinquency history, in highly opioid-affected counties. Also importantly, within a county, minorities, particularly Black people, receive worse credit terms than others. Low-income individuals, those with income less than $30k, are also treated much more harshly by lenders. Young people, those under the age of 25, are also charged higher rates in high exposure areas. The effects on their credit limits are negative but not statistically significant.

6.5 Credit Card Rewards and Likelihood of Credit Card Offers

The Mintel dataset also allows us to measure another element of credit pricing; that is, offers of rewards/promotions, in addition to credit supply on the extensive margin, credit card offer likelihood. We thus repeat our analyses using credit card rewards and credit card offer likelihood as our dependent variables and report the IV 2SLS second stage results in Table 9. Note that for credit card rewards, we use the same offer-level sample as above, while for likelihood of credit card offer, we use an extended larger sample that includes consumers with and without offers in each month. Our analyses reveal that individuals in higher exposure counties are less likely to receive credit card rewards and promotions by 4 percentage points, which may have implications on consumer total price of credit and their ex-post spending behavior. Importantly, credit card offer likelihood also declines significantly in counties with higher opioid abuse. Here, results imply a 10 percentage points reduction.

6.6 Effectiveness of Recent Opioid Policies

Given the severity of the opioid crisis and its adverse economic impact, a number of opioid-related laws and regulatory reactions emerged in recent years in an effort to try to combat negative effects of the opioid epidemic. Their effectiveness is largely understudied with a few studies that attempt to estimate the implications of those regulations either yielding mixed results or considering only one such law at a time, making it difficult to draw impactful policy conclusions. For example, Kaestner and Engy (2019) find that Prescription Drug Monitoring Programs (PDMPs) reduce prescription rates, but do not help reduce opioid deaths or improve socioeconomic outcomes. In contrast, Cornaggia, Hund, Nguyen and Ye (2021) find that adoption of PDMPs reduces opioid deaths and also partially reverses some negative effects on municipal finance. Doleac and Mukherjee (2019) find increased opioid abuse after increased access to naloxone (which reverses opioid overdose), likely due to increasing risk taken by opioid addicts given they know there is an antidote in place to save their lives.

We add to this debate and the related literature by investigating the effects of six different opioid-related laws on consumers and consumer finance outcomes, out of which three are opioid supply-oriented laws and the other three are demand/user oriented opioid laws. Among the six laws, four are time-varying with a staggered implementation and two are time-invariant over our sample period. We focus on the impact on consumer credit supply, as this is the margin that has the most implications on local economic recovery.

We first describe the supply-related laws, out of which the first two are time varying, while the last one is time invariant. First, the "State Opioid Limiting Laws" explicitly set limits on prescriptions of opioids. For instance, certain states would limit prescriptions to a four-, five-, or seven-day supply for first time users or for acute or postoperative pain or other uses or set other limits on the number of prescriptions or overall quantity of opioids that can be prescribed by physicians to a patient. As of 2018, 32 states had such legislation limits in place. We collect these data from Custodio, Cvijanovic and Wiedemann (2021) and complement with more recent updates for individual states from other public sources such as the National Conference of State Legislatures (NCSL) and individual state government websites. Second, the "PDMP Laws" collect and track opioid prescriptions and connect prescribers, dispensers, law enforcement, and Medicare authorities. The ultimate goal of PDMPs is to enable doctors to better monitor and identify drug-seeking patients. Some states mandate the use of PDMPs by prescribers while others make it voluntary, with potential different effects on effectiveness in combating opioid abuse. We obtain information on these laws from the Prescription Drug Monitoring System and the Opioid Environment Policy Scan (OEPS) from University of Chicago.[24] We focus on the mandatory PDMPs in our analysis given prior research finds these to be more likely to affect behavior, but also conduct robustness using all the PDMPs and find consistent results. Finally, a time-invariant supply law, the "Triplicate Prescription Law," required that three copies of an opioid prescription be issued: The prescriber keeps one copy, another is kept by the pharmacist, while the third is sent to a state agency by the pharmacist. Alpert, Evans, Lieber and Powell (2022) show how strict monitoring of opioid pre-

[24] See Opioid Environment Policy Scan Data Warehouse (v1.0), https://doi.org/10.5281/zenodo.5842465.

scriptions via special prescription documentation in triplicate requirement substantially reduces opioid use and related deaths in those states once an epidemic unfolds. The requirement was in effect in the states of California, Idaho, Illinois, New York, and Texas.

Then, we discuss the demand/user related opioid laws; again the first two are time varying, while the last one is time invariant. First, the Naloxone Law increases access to and allow the prescribing and dispensing of naloxone (an opioid receptor antagonist that reverses opiate overdose) by various third parties to users with documented risk factors for overdose, which may help reduce some opioid deaths (e.g., Davis and Carr (2015)). Then, the "Good Samaritan Law" provides immunity to drug users for certain drug crimes when they call for help for a person experiencing a drug overdose, again potentially helping reduce deaths. Finally, a time-invariant law is the Medical Marijuana Permitting Law. Its effects on opioid overdoses were highly debated, in which initial studies showed a decline in overdoses in medical marijuana permitting states, but later studies documented a reversal increasing rather than decreasing opioid overdose deaths (e.g., Shover, Davis, Gordon and Humphreys (2019)).[25] The two laws are time-invariant over our sample period.

We first take advantage of the staggered implementation of the four state-level opioid laws designed to combat opioid abuse (two being supply-oriented and two being demand-oriented laws) by running a difference-in-difference (DID) regression specification to evaluate the effectiveness of the laws and their influence on consumers and consumer finance. For the time-invariant supply and demand laws, we use simplified fixed effects and/or sample splits, whichever specification is strongest and possible to employ.

We first examine the effects of opioid laws on prescription and opioid mortality rates, including total, prescription mortality, and illicit mortality rates, and report results in Table 10 Panel A using county-level regressions over 2010-2019, while including all county controls from our main specifications and additional fixed effects. The fixed effects include county, state, and year for the effects of opioid-time-varying laws, and only year fixed effects for the state time-invariant ones, given that the laws are at the state level. We group laws in the regression by whether they are supply related or demand/user related laws for ease of interpretation and also because the two

[25] The Good Samaritan and Medical Marijuana Laws data are from the Opioid Environment Policy Scan (OEPS) from the University of Chicago.

types have very different targets.

Conditional on a strong set of controls for local markets and time, we uncover very different impacts among the supply and demand-oriented opioid laws. Specifically, we observe that all supply-related laws have some beneficial effects in reducing opioid prescriptions and prescription opioid death rates, with the opposite impact on the opioid illegal and, hence, total deaths. This may seem reasonable, as the laws passed rarely can help dissuade illegal drug activities in various local markets. An exception is the triplicate law, which tends to attenuate opioid deaths from both prescription and illegal sources, likely due to very strict and unfavorable environments for opioids in these states. Turning to the three demand/user laws, only the Medical Marijuana Permitting Law was able to reduce both the opioid prescription rates and the opioid prescription related death rates. These initial results establish that not all laws are the same, which is consistent also with the mixed findings on deaths in prior research. Thus, we can expect different effects in reversing consumer credit outcomes as well.[26]

Table 10 Panel B conducts a horse race among the effects of different state laws on consumer credit supply. As mentioned, we again group the laws into those that affect opioid supply: Opioid Limiting Law and Opioid PDMP Law; and those that affect opioid demand: Naloxone Law and Samaritan Law. We show the effects of time-varying state laws in Panel B1, and sample splits for the time-invariant laws in Panels B2 and B3. Our key dependent variables are interest rate spreads and credit card limits, while we also include our main opioid intensity measures, all consumer and county controls, and fixed effects as in our main analyses. Same as above, we instrument opioid intensity with *MKTDoctors/1000Pop*, and report IV 2LS second stage estimates in all cases.

Table 10 Panel B1 shows that the supply-related laws — the Opioid Prescription Limiting Law and the mandatory PDMP Law — both yield positive effects on consumer credit supply, which reverse some of the negative consequences of the opioid crisis, while the demand-related laws — the Naloxone Law and the Good Samaritan Law — have either no effects or some negative effects on credit supply for consumers. Finally, Panels B2 and B3 show that there are no negative effects on rates but there are negative effects on credit limits for consumers in states that implemented the supply-related Triplicate Prescription Law. By comparison, in states that did not

[26]Results are similar in a sample that starts earlier in 2007 instead of 2010.

implement the law, the negative effects show up in both dimensions and are much larger. We also find that only states that implemented the demand-related law "Medical Marijuana Permitting Law" yield negative credit supply effects. To conclude, the supply-related laws (the opioid prescription limiting law, the mandatory PDMPs, and the triplicate prescription law) all tend to have positive reversal effects on consumer market credit supply, while the demand-related laws (Naloxone, Good Samaritan, Medical Marijuana Permitting Laws) appear to help less or even induce some detrimental effects on consumer credit, and potentially intensify the opioid crisis.[27] Importantly, we found that the supply-related laws that do have beneficial effects on reducing opioid prescriptions and deaths also tend to exhibit mitigating effects in consumer credit supply.

6.6.1 Possible Underlying Mechanisms for Credit Supply

To understand our credit supply results, we next investigate consumer credit performance as well as bank portfolio risk and how they vary with their exposure to the opioid epidemic.

6.6.1.1 Consumer Credit Performance

For consumer credit performance, we make use of information from FR Y14-M on credit cards accounts' days past due, bank-estimated loan probability of default (PD), the monthly payments made by consumers, as well as their refreshed credit scores. We aggregate the information to the bank-county-year-month level to arrive at averages for the bank-county for each given year-month.

The results are reported in Table 11 Panel A. We observe that borrowers in high opioid exposure counties tend to have longer days of past due, higher bank-assessed loan probability of default (PD), lower monthly payments, and lower updated credit scores. These results suggest significant credit risk associated with consumers living in areas with high opioid exposure. Those people are either more likely to abuse opioids if they live in the high-exposure counties or may be more financially vulnerable to opioid abuse in those counties. As we discussed in the Introduction and the Literature Review, opioid abuse reduces individuals' employment as well as firms' hiring.

[27] The different effects are likely due to the different nature and intent of the laws, and are somewhat consistent with prior research.

This labor channel alone would lead to enhanced credit risk, according to the model presented earlier. Most importantly, the evidence here suggests that credit card borrowers in highly exposed areas pose significant credit risk for the lenders, which may explain some of their cautious credit supply behavior. In the Appendix Table A3 Panel A we repeat our analyses using county-year-month observation, our results are robust.

6.6.1.2 Bank Consumer Loan Portfolio Performance

Given that consumers in areas hard-hit by opioids are more likely to default on their financial obligations, we next test whether banks more exposed to the opioid crisis via their local branch network or operations suffer more from nonperforming loans across their consumer loan portfolios. Specifically, we test whether exposed banks that operate in only one county and are likely to have a harder time diversifying their risk exposure from the opioid crisis may suffer from credit risk in their portfolios. Our estimation results are reported in Table 11 Panel B, where we examine credit card nonperforming loans ratio as well as nonperforming loans ratios for unsecured consumer credit using IV 2SLS analysis and the same instrument we use above. Our second stage IV estimates show that banks confined to more severely affected counties report higher nonperforming loans in credit card products as well as total unsecured consumer loans. This evidence further helps corroborate our story that banks experience more materialized credit risk in their loan portfolios, hence the decline in credit supply to opioid-affected areas.

6.6.2 The Real Effects of the Opioid Crisis - Consumer Spending

Before we conclude, we reconfirm our main credit supply effects using the supervisory FR Y-14M dataset and also explore the likely possible macro real effects of the opioid crisis, in both cases using the same IV 2SLS analysis employed throughout our study. In these analyses we use a bank-county-year-month sample. We construct several measures of consumption: total purchases per county population, average total purchases relative to credit limit, and average account purchases in both logged and unlogged forms.

Our estimation results are reported in Table 12. Panel A reports effects of the opioid crisis intensity on elements of credit supply, including average cycle APR, limit per county population, average limit, and percent of accounts with rewards. Panel B reports effects on consumer spending proxied by the credit card purchases made by consumers as provided by FR Y-14M. Our second stage IV estimates in Panel A reconfirm that credit supply declines in counties more affected by the opioid crisis as evidenced by higher cycle APRs, lower limits, and fewer accounts with rewards. Then, in Panel B, we find that counties with high opioid exposure suffered much more in credit card spending. For example, the average purchase is about $865 lower in bank-counties with opioid death rates in the top 50th percentile of the nation than in counties with death rates in the lower 50th percentile of the nation. These effects are even larger when re-estimating the effects using an aggregated county-year-month sample but without the lender year-month fixed effects as shown in Appendix Table A3 Panel C, implying average purchase declines per county by as much as $1,200 in more affected counties.

7 Conclusions

The opioid epidemic in the U.S. has left far-reaching and lingering consequences on the health and social conditions of U.S. local communities for over two-and-a-half decades. In this paper, we discover unfavorable credit supply consequences of this crisis on consumers: banks are reluctant to lend in areas with significant exposure to opioids. They are less likely to send credit offers in the exposed areas; however, when they do still solicit consumers for credit in those areas, the offers have much higher interest rates, lower credit limits, and fewer rewards/promotions. The credit supply constriction seems to harm harder the riskier consumers, minorities (particularly Black people), low-income people, and younger consumers.

The wave of laws and regulations passed to reduce the devastating effects of the opioid crisis on communities raises a question whether the legislative effort helped mitigate some of the negative effects uncovered in the study. Our analysis of 6 different opioid-related laws (three supply-related and three demand/user related laws) suggests different effects across supply- and demand-oriented laws in mitigating both the crisis and credit supply effects on consumers. The opioid supply laws (prescription limiting law, the mandatory PDMP, and the triplicate prescription law) all appear to mitigate some of the negative impacts of the opioid epidemic on consumers and their credit supply, while the demand-related laws are less beneficial or can even aggravate the opioid crisis.

From a policy standpoint, the cautious behavior of banks appears to be partially justified by the relatively high credit risk in the highly affected areas. The reduced consumer credit supply, nevertheless, could create a negative feedback loop depriving the opioid-affected regions of the much-needed liquidity for recovery. Indeed, we find that the opioid-crisis induced credit supply contraction may have some important real effects: Consumer spending sharply decreases in harder-hit local markets. This latter may suggest important macro-policy implications given that consumer spending accounts for the vast majority of US gross domestic product and economic growth. Thus, it is natural to ask: where should we go from here, i.e., "quo vadis." The findings here may be useful for policymakers in better understanding the impact of the opioid crisis and formulating adequate policies concerning consumers to help recovery efforts, enhance welfare, and restore growth and resilience in opioid-affected consumer markets.

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Figure 1 : Opioid-Related Death Rates Over Time

This line chart depicts the time trend of total opioid-related death rates, illicit opioid-related death rates, and prescription opioid-related death rates per 10k population. Data sources: CDC/NCHS, National Center for Health Statistics, Mortality, restrictive version for 2010-2019, and the public version for 2020.

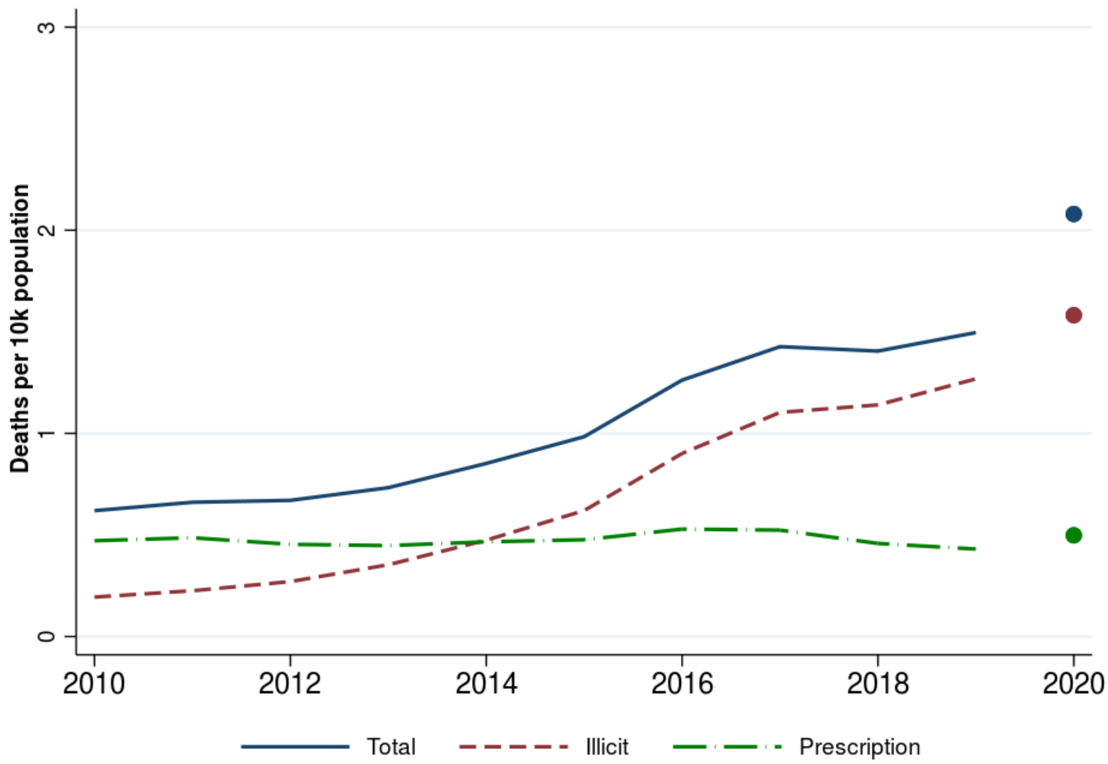
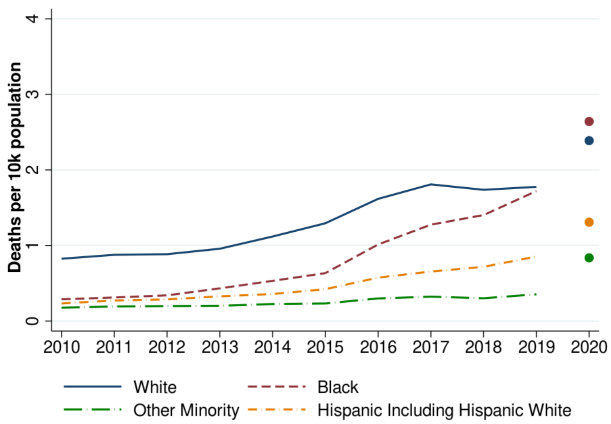


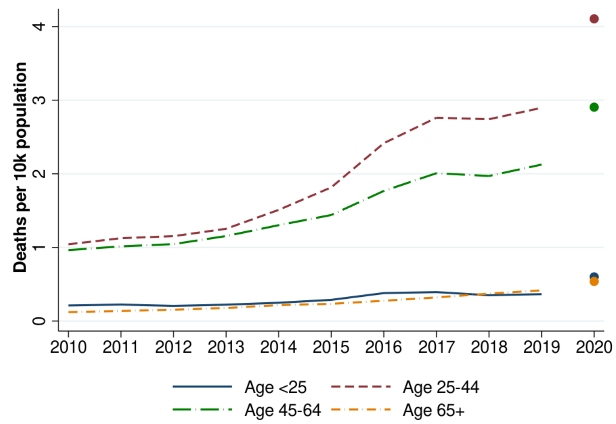
Figure 2 : Opioid Death Rates by Consumer Demographics

This figure plots overall opioid-related death rates per 10K population by consumer demographics (age groups, gender, race groups, and education groups) over time. Rates are constructed relative to their respective population. Data sources: CDC/NCHS, National Center for Health Statistics, Mortality, restrictive version for 2010-2019, and the public version for 2020. The public version doesn't contain information by education.

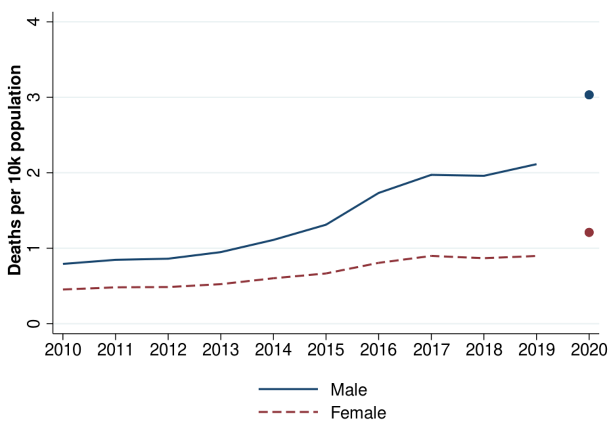
Panel A. Opioid Death Rates by Consumer Race



Panel B. Opioid Death Rates by Consumer Age



Panel C. Opioid Death Rates by Consumer Gender



Panel D. Opioid Death Rates by Consumer Education

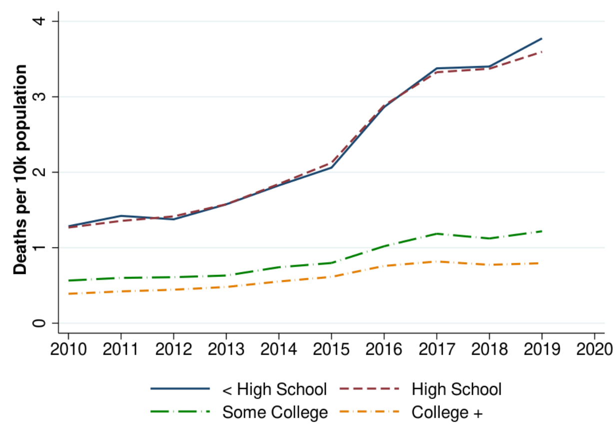


Figure 3 : Opioid-Related Death Rates across U.S. Counties

This figure presents the geographical distribution of opioid-related death rates (per 10K population) across U.S. counties for year 2019. Darker red colors represent higher death rates. Data sources: CDC/NCHS, National Center for Health Statistics, Mortality.

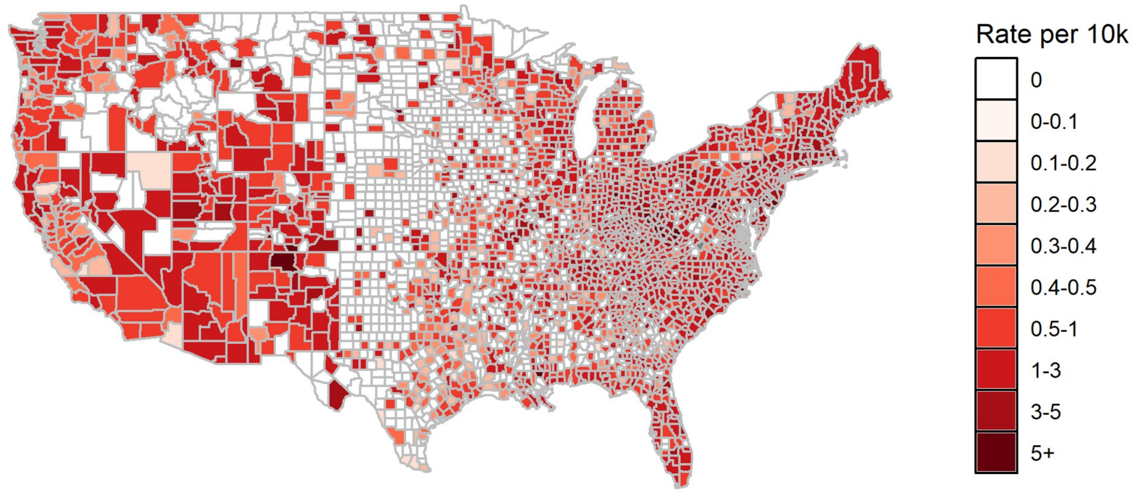


Figure 4 : Instrument "MKT Doctors/1000Pop" across U.S. Counties

This figure presents the geographical distribution of physicians receiving pharmaceutical industry marketing for opioids across U.S. counties over 2013-2019. The figure presents 10 categories that were obtained based on an equal deciles' methodology, with darker colors representing higher marketing rates; 1 indicates that the counties' marketing rates ranked in the bottom decile of the country, while 10 indicates that the counties' marketing rates ranked in the top decile of the nation. Thus, darker colors show higher opioid marketing intensity. Data sources: Open Payments Database and Hadland, Rivera-Aguirre, Marshall and Cerda (2019).

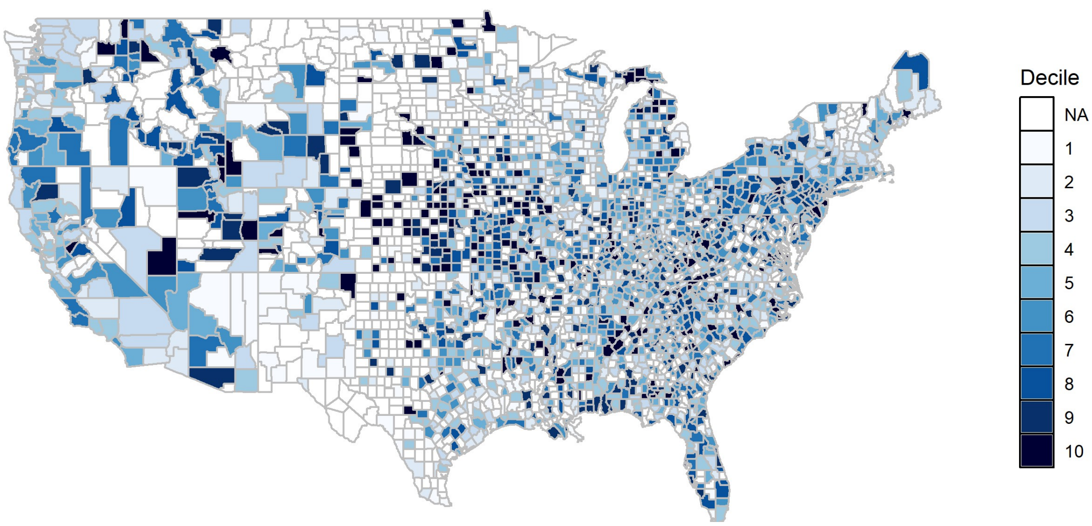


Figure 5 : Validating the Instrument: Relevancy

This figure provides binned scatter plot of opioid-related deaths per 10K population versus pharmaceutical industry opioid drug marketing (doctors receiving marketing payments per 1,000 people, *MKT Doctors/1000Pop*) after taking out the state and year fixed effect. Data sources: CDC/NCHS, National Center for Health Statistics, Mortality, CDC/IQVIA Xponent, Hadland, Rivera-Aguirre, Marshall and Cerda (2019), Open Payments Database, U.S. Drug Enforcement Administration (DEA) and Cornaggia, Hund, Nguyen and Ye (2021).

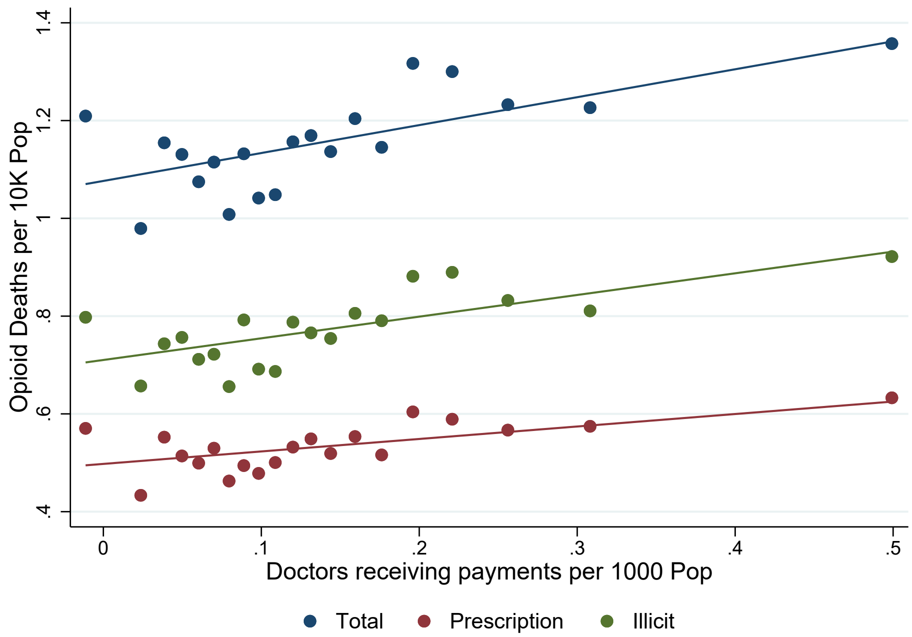


Table 1: Summary Statistics

This table reports in Panel A summary statistics (mean, p50, p25, p75, and number of observations) for the key variables in our analyses. Variable definitions and data sources are in Appendix Table A1. The sample is based on the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card supply to consumers. The data are focused on institutions identified as "banks" in the Mintel/TransUnion Match File. All demographic attributes are from Mintel. Panel B shows correlations of our instrumental variable (*MKT Doctors/1000Pop* with county economic and other characteristics.

Panel A: Mintel/TransUnion Match File Variables

	mean	p50	std	p25	p75	N
Dependent Variables						
Rate Spread	17.305	15.760	5.076	12.970	22.770	197,371
Ln(Limit)	6.447	6.217	0.776	6.217	6.909	197,371
Limit ($)	941.145	500.000	1170.751	500.000	1000.000	197,371
Rewards/Promo	0.900	1.000	0.300	1.000	1.000	197,371
Credit Card Offer	0.564	1.000	0.496	0.000	1.000	392,101
Key Independent Variables						
Opioid Death Rate	1.212	0.916	1.025	0.526	1.573	197,371
High Opioid Death Rate	0.513	1.000	0.500	0.000	1.000	197,371
Prescription Opioid Death Rate	0.500	0.416	0.393	0.229	0.650	197,371
Illicit Opioid Death Rate	0.864	0.542	0.943	0.258	1.126	197,371
Opioid Prescription Rate	0.721	0.684	0.295	0.505	0.869	197,350
Instrumental Variables						
MKT Doctors/1000Pop	0.140	0.120	0.093	0.072	0.188	197,371
MKTPayments/1000Pop	0.542	0.417	0.459	0.201	0.752	197,371
Purdue MKT (Oxycontin Growth '97-'02)	6.020	5.211	3.510	3.760	7.315	369,169
Consumer Controls						
Consumer Credit Score	702.980	699.000	92.653	633.000	782.000	197,371
Credit Score_580_660	0.267	0.000	0.442	0.000	1.000	197,371
Credit Score_660_720	0.209	0.000	0.406	0.000	0.000	197,371
Credit Score_720_800	0.243	0.000	0.429	0.000	0.000	197,371
Credit Score_800plus	0.194	0.000	0.395	0.000	0.000	197,371
Deep_Delinq	0.213	0.000	0.410	0.000	0.000	197,371
Recent_Delinq	0.085	0.000	0.278	0.000	0.000	197,371
Other_Derogatory	0.235	0.000	0.424	0.000	0.000	197,371
Bankruptcy_Filer	0.067	0.000	0.251	0.000	0.000	197,371
High_Util ($\geq$80%)	0.024	0.000	0.155	0.000	0.000	197,371
Ln(1+ No Credit Inquiries)	0.336	0.000	0.517	0.000	0.693	197,371
Has_Prior_Cards	0.940	1.000	0.237	1.000	1.000	197,371
Consumer Age	49.779	50.000	15.706	37.000	61.000	197,371
Age_25to44	0.355	0.000	0.479	0.000	1.000	197,371
Age_45to64	0.418	0.000	0.493	0.000	1.000	197,371
Age_65plus	0.186	0.000	0.389	0.000	0.000	197,371
Married	0.310	0.000	0.462	0.000	1.000	197,371
No_Kids	0.406	0.000	0.491	0.000	1.000	197,371
White	0.410	0.000	0.492	0.000	1.000	197,371
Miss_Race	0.501	1.000	0.500	0.000	1.000	197,371
Educ: Some_College	0.105	0.000	0.307	0.000	0.000	197,371
Educ: College	0.122	0.000	0.328	0.000	0.000	197,371
Educ: Post_College	0.058	0.000	0.234	0.000	0.000	197,371
Miss Educ	0.317	0.000	0.465	0.000	1.000	197,371
Homeowner	0.753	1.000	0.431	1.000	1.000	197,371
Ln(Consumer Income)	10.958	11.082	0.821	10.532	11.379	197,371

Table 1: Summary Statistics (cont.)

This table reports in Panel A summary statistics (mean, p50, p25, p75, and number of observations) for the key variables in our analyses. Variable definitions and data sources are in Appendix Table A1. The sample is based on the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card supply to consumers. The data are focused on institutions identified as "banks" in the Mintel/TransUnion Match File. All demographic attributes are from Mintel. Panel B shows correlations of our instrumental variable (*MKT Doctors/1000Pop* with county economic and other characteristics.

Panel A: Mintel/TransUnion Match File Variables (cont.)

	mean	p50	std	p25	p75	N
County Controls						
Ln(County Income)	16.922	17.040	1.493	15.871	17.979	197,371
County Unemployment Rate	4.900	4.633	1.580	3.800	5.700	197,371
County Bank HHI	0.174	0.144	0.107	0.114	0.189	197,371
County Population Density	1882.788	688.603	5495.129	255.714	1671.863	197,371
County Race HHI	0.679	0.668	0.197	0.540	0.795	197,371
County % Male	0.491	0.490	0.010	0.485	0.495	197,371
County % Age_25_44	0.263	0.262	0.032	0.242	0.284	197,371
County % Age_45_64	0.265	0.265	0.024	0.249	0.281	197,371
County % Age_65plus	0.144	0.139	0.037	0.121	0.160	197,371
County % High Education ($\geq$ College)	0.601	0.606	0.089	0.543	0.662	197,371
County Inequality: Gini Coefficient	0.457	0.457	0.034	0.434	0.479	197,371

Panel B: Correlations of Instrument with County-Level Conditions

MKT Doctors/1000Pop	Correlation Coefficient
County Personal Income	-0.018
County per Capita Income	-0.001
County HPI Growth	-0.038
County Labor Participation Rate	-0.023
County Unemployment Rate	-0.068
County Average FICO Score	0.025
County Poverty Rate	0.019
County Crime Rate	-0.008
County Population Density	0.008
County Population	-0.028
County Race HHI	-0.023
County % Male	-0.122
County Average Age	0.117
County % High Education ($\geq$ College)	0.033
County Inequality: Gini Coefficient	0.122

Table 2: Effects of the Opioid Crisis on Credit Card Supply to Consumers

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports the first-stage IV and Panel B reports second-stage IV estimates from offer-level regressions. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month, Lender × Year-Month, Lender × State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate
Model:	(1)	(2)
Mkt Doctors/1000Pop$_{c,t-1}$	1.0349***	0.4511***
	(21.65)	(12.85)
Fit statistics		
Observations	197,371	197,371
Adj. R^2	0.559	0.421
Fixed effects		
State × Year-Month	✓	✓
Lender × Year-Month	✓	✓
Lender × State	✓	✓
Lender, State, Year-Month	✓	✓
Consumer & County controls	✓	✓

Panel B: IV Second Stage

Dependent Variables:	Rate Spread	Ln(Limit)	Limit ($)	Rate Spread	Ln(Limit)	Limit ($)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$	0.5191***	-0.0720***	-84.4863***			
	(4.95)	(-3.58)	(-2.77)			
High Opioid Death Rate$_{c,t-1}$				1.1909***	-0.1652***	-193.8267***
				(4.92)	(3.58)	(-2.77)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.317	0.157	0.083	0.311	0.154	0.081
IV first-stage statistics						
KP rk Wald F-stat (Weak-ID)	1787***	1787***	1787***	1786***	1786***	1786***
KP rk LM-stat (Under-ID)	1782***	1782***	1082***	1087***	1087***	1087***
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 3: Using Prescription and Illicit Opioid Deaths

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity (*Prescription Opioid Death Rate, High Prescription Death Rate* and *Illicit Death Rate, High Illicit Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports the first-stage IV and Panel B reports second-stage IV estimates from offer-level regressions. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month, Lender × Year-Month, Lender × State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

Dependent Variables:	Prescription Opioid Death Rate	High Prescription Opioid Death Rate	Illicit Opioid Death Rate	High Illicit Opioid Death Rate
Model:	(1)	(2)	(3)	(4)
Mkt Doctors/1000Pop$_{c,t-1}$	0.6190***	0.8977***	0.6316***	0.2549***
	(25.96)	(27.88)	(14.37)	(8.46)
Fit statistics				
Observations	197,371	197,371	197,371	197,371
Adj. R^2	0.429	0.329	0.615	0.491
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Panel B: IV Second Stage

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prescription Opioid Death Rate$_{c,t-1}$	0.8679***	-0.1204***						
	(4.96)	(-3.59)						
High Prescription Opioid Death Rate$_{c,t-1}$			0.5984***	-0.0830***				
			(4.96)	(-3.59)				
Illicit Opioid Death Rate$_{c,t-1}$					0.8505***	-0.1180***		
					(4.91)	(-3.57)		
High Illicit Opioid Death Rate$_{c,t-1}$							2.1072***	-0.2922***
							(4.83)	(-3.55)
Fit statistics								
Observations	197,371	197,371	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.321	0.159	0.321	0.160	0.308	0.152	0.285	0.139
Fixed effects								
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓	✓	✓

Table 4: Using Opioid Prescription Rate

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity (*Opioid Prescription Rate* and *High Opioid Prescription Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports the first-stage IV and Panel B reports second-stage IV estimates from offer-level regressions. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month, Lender* × *Year-Month, Lender* × *State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

Dependent Variables:	Opioid Prescription Rate	High Opioid Prescription Rate
Model:	(1)	(2)
Mkt Doctors/1000Pop$_{c,t-1}$	0.9671***	1.3144***
	(55.93)	(44.64)
Fit statistics		
Observations	197,367	197,367
Adj. R^2	0.739	0.538
Fixed effects		
State × Year-Month	✓	✓
Lender × Year-Month	✓	✓
Lender × State	✓	✓
Lender, State, Year-Month	✓	✓
Consumer & County controls	✓	✓

Panel B: IV Second Stage

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)
Opioid Prescription Rate$_{c,t-1}$	0.5578***	-0.0769***		
	(4.99)	(-3.59)		
High Opioid Prescription Rate$_{c,t-1}$			0.4104***	-0.0565***
			(4.99)	(-3.58)
Fit statistics				
Observations	197,367	197,367	197,367	197,367
Adj. R^2	0.325	0.162	0.325	0.162
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Table 5: Using Different Instrumental Variables (IVs)

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using two alternative instrumental variables (IVs), ”Mkt Payments/1000Pop” and ”High Purdue Mkt” for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports the IV estimates using ”Mkt Payments/1000Pop” as instrument and Panel B reports IV estimates using ”High Purdue Mkt” as instrument from offer-level regressions. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as ”banks” in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month, Lender* × *Year-Month, Lender* × *State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Using ”Mkt Payments/100Pop” as IV

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Rate Spread	Ln (Limit)	Rate Spread	Ln (Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mkt Doctors/1000Pop$_{c,t-1}$	0.3004***	0.1095***				
	(24.67)	(19.73)				
Opioid Death Rate$_{c,t-1}$			0.2814***	-0.0311**		
			(4.00)	(-2.31)		
High Opioid Death Rate$_{c,t-1}$					0.7723***	-0.0854**
					(3.99)	(-2.31)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.564	0.422	0.323	0.162	0.319	0.161
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Panel B: Using ”High Purdue Mkt” as IV

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Rate Spread	Ln (Limit)	Rate Spread	Ln (Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
High Purdue Mkt$_{c,t-1}$	0.0512***	0.0079***				
	(14.81)	(3.46)				
Opioid Death Rate$_{c,t-1}$			0.7834***	-0.1224*		
			(2.89)	(-1.95)		
High Opioid Death Rate$_{c,t-1}$					5.0599**	-0.7904*
					(2.37)	(-1.77)
Fit statistics						
Observations	369,162	369,162	369,162	369,162	369,162	369,162
Adj. R^2	0.544	0.343	0.250	0.097	-0.115	-0.101
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 6: More Identification: Propensity Score Matching (PSM) & Contiguous Counties

This table reports estimates from both univariate results and IV 2SLS regression results (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports univariate evidence and Panels B and C report second-stage IV regression estimates from PSM analyses, where counties with a high opioid death rate (top 25%) are matched using several techniques (1:1 matching without replacement, 1:1 matching with replacement, nearest neighbor (n=2), nearest neighbor (n=3), and nearest neighbor (n=5)) to counties with a low opioid death rate, based on similar characteristics, including the instrument "Mkt Doctors/1000Pop". Finally, Panel D reports IV regression estimates when using contiguous counties only to the counties with a high opioid death rate (top 25%). All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month, Lender × Year-Month, Lender × State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Univariate Evidence using Different PSM Methods

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Rate Spread				Ln(Limit)			
PSM Estimation (common support)	Treated	Control	Difference	t-stat	Treated	Control	Difference	t-stat
1:1 Matching without replacement	17.46	17.24	0.22	7.11***	6.425	6.44	-0.015	-3.18***
1:1 Matching with replacement	17.46	16.98	0.48	4.16***	6.425	6.53	-0.105	-5.85***
Nearest neighbor (n=2)	17.46	17.2	0.26	3.01***	6.425	6.48	-0.055	-4.18***
Nearest neighbor (n=3)	17.46	17.25	0.21	2.88***	6.425	6.469	-0.044	-3.88***
Nearest neighbor (n=5)	17.46	17.23	0.23	3.76***	6.425	6.459	-0.034	-3.56***

Panel B: IV 2SLS with PSM Sample (1:1 Matching without replacement)

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Rate Spread	Ln (Limit)	Rate Spread	Ln (Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mkt Doctors/1000Pop$_{c,t-1}$	0.5168***	0.2672***				
	(6.83)	(6.93)				
Opioid Death Rate$_{c,t-1}$			1.0998***	-0.2700***		
			(3.84)	(-4.80)		
High Opioid Death Rate$_{c,t-1}$					2.1276***	-0.5222***
					(3.86)	(-4.84)
Fit statistics						
Observations	100,576	100,576	100,576	100,576	100,576	100,576
Adj. R^2	0.471	0.298	0.263	0.027	0.271	0.046
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 6: Propensity Score Matching (PSM) & Contiguous Counties (cont.)

This table reports estimates from both univariate results and IV 2SLS regression results (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports univariate evidence and Panels B and C report second-stage IV regression estimates from PSM analyses, where counties with a high opioid death rate (top 25%) are matched using several techniques (1:1 matching without replacement, 1:1 matching with replacement, nearest neighbor (n=2), nearest neighbor (n=3), and nearest neighbor (n=5)) to counties with a low opioid death rate, based on similar characteristics, including the instrument "Mkt Doctors/1000Pop". Finally, Panel D reports IV regression estimates when using contiguous counties only to the counties with a high opioid death rate (top 25%). All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel C: IV 2SLS with PSM Sample (1:1 Matching with replacement)

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Rate Spread	Ln (Limit)	Rate Spread	Ln (Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mkt Doctors/1000Pop$_{c,t-1}$	0.4591***	0.1398**				
	(3.19)	(2.31)				
Opioid Death Rate$_{c,t-1}$			2.5353***	-0.1241**		
			(7.48)	(-2.36)		
High Opioid Death Rate$_{c,t-1}$					8.3256***	-0.4074**
					(6.16)	(-2.31)
Fit statistics						
Observations	101,145	101,145	101,145	101,145	101,145	101,145
Adj. R^2	0.531	0.449	0.001	0.170	0.474	0.136
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Panel D: IV 2SLS using Contiguous Counties Only

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Rate Spread	Ln (Limit)	Rate Spread	Ln (Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Mkt Doctors/1000Pop$_{c,t-1}$	0.9774***	0.3058***				
	(7.44)	(7.42)				
Opioid Death Rate$_{c,t-1}$			1.0145***	-0.1402***		
			(4.76)	(-3.48)		
High Opioid Death Rate$_{c,t-1}$					3.2420***	-0.4481***
					(4.78)	(-3.49)
Fit statistics						
Observations	64,276	64,276	64,276	64,276	64,276	64,276
Adj. R^2	0.601	0.366	0.278	0.131	0.284	0.139
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 7: Heterogeneous Effects for High Credit Risk Consumers

This table examines how the effects of opioid crisis intensity on bank credit card terms (rate spread and credit card limit) differ by consumer credit risk using interactions of consumer "High Credit Risk" and opioid intensity. We define "High Credit Risk" as either "Subprime" (Credit Score <620) in Panel A or "Deep Delinquency" past 90+ days past due (DPD)) in Panel B. We report regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" as an instrument for opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*), based on data from the CDC). All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month, Lender* × *Year-Month, Lender* × *State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Subprime (Credit Score <620)

Dependent Variables:	Rate Spread	Ln(Limit)	Limit ($)	Rate Spread	Ln(Limit)	Limit ($)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$ x High Credit Risk$_{i,c,t-1}$	0.1320***	-0.0150***	-9.2690**			
	(9.38)	(-5.87)	(-2.42)			
High Opioid Death Rate$_{c,t-1}$ x High Credit Risk$_{i,c,t-1}$				2.9878***	-0.3405***	-212.6968**
				(9.45)	(-5.96)	(-2.49)
Opioid Death Rate$_{c,t-1}$	0.2567**	-0.0374*	-64.5647*			
	(2.11)	(-1.69)	(-1.94)			
High Opioid Death Rate$_{c,t-1}$				0.6788**	-0.0958*	-153.6938**
				(2.46)	(-1.92)	(-2.06)
High Credit Risk$_{i,c,t-1}$	0.3853**	-0.0463	-121.2126**	0.4633***	-0.0550*	-125.8480***
	(2.22)	(-1.46)	(-2.56)	(2.80)	(-1.84)	(-2.81)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.208	0.118	0.063	0.196	0.115	0.108
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Panel B: Deep Delinquency (90+ DPD)

Dependent Variables:	Rate Spread	Ln(Limit)	Limit ($)	Rate Spread	Ln(Limit)	Limit ($)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$ x High Credit Risk$_{i,c,t-1}$	0.1509***	-0.0136***	-4.8549			
	(11.08)	(-5.31)	(-1.26)			
High Opioid Death Rate$_{c,t-1}$ x High Credit Risk$_{i,c,t-1}$				3.1775***	-0.2894***	-110.594
				(11.25)	(-5.48)	(-1.39)
Opioid Death Rate$_{c,t-1}$	0.1864	-0.0440**	-79.9785**			
	(1.62)	(-2.03)	(-2.46)			
High Opioid Death Rate$_{c,t-1}$				0.4822*	-0.1050**	-183.0233**
				(1.85)	(-2.16)	(-2.50)
High Credit Risk$_{i,c,t-1}$	-0.2803*	-0.0379	-153.6166***	-0.0931	-0.0529**	-154.4175***
	(-1.72)	(-1.24)	(-3.34)	(-0.65)	(-1.98)	(-3.83)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.278	0.141	0.08	0.268	0.138	0.077
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 8: Heterogeneous Effects for Minority, Low Income, and Young Consumers

This table examines how the effects of opioid crisis intensity on bank credit card terms differ by consumer race, income, and age using interactions of consumer race/minority and opioid intensity in Panels A and B, and interactions of consumer low income ($\leq$\$30k) and young ($\leq$25 yrs) with opioid intensity in Panels C and D. In all cases, we report IV 2SLS regression estimates (equations (3) and (4)) using "Mkt Doctors/1000Pop" as an instrument for opioid crisis intensity. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Minority Consumers

Dependent Variables:	Rate Spread	Ln(Limit)	Limit (\$)	Rate Spread	Ln(Limit)	Limit (\$)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$ x Minority$_{i,c,t}$	0.0176	-0.0058**	-6.3736*			
	(1.32	(-2.26)	(-1.65)			
High Opioid Death Rate$_{c,t-1}$ x Minority$_{i,c,t}$				0.4314	-0.1316**	-146.0764*
				(1.5)	(-2.40)	(-1.76)
Opioid Death Rate$_{c,t-1}$	0.4902***	-0.0625***	-74.0231**			
	(4.43)	(-2.95)	(-2.30)			
High Opioid Death Rate$_{c,t-1}$				1.1179***	-0.1429***	-169.0837**
				(4.42)	(-2.96)	(-2.31)
Minority$_{i,c,t}$	0.068	0.0287	35.6529	0.0599	0.0258	32.7751
	(0.48)	(1.06)	(0.87)	(0.48)	(1.08)	(0.90)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.317	0.157	0.083	0.312	0.154	0.081
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Panel B: Black, Hispanic, Other Minority Consumers

Dependent Variables:	Rate Spread	Ln(Limit)	Limit (\$)	Rate Spread	Ln(Limit)	Limit (\$)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$ x Black$_{i,c,t}$	0.0657***	-0.0126***	-14.7536**			
	(2.81)	(-2.81)	(-2.17)			
Opioid Death Rate$_{c,t-1}$ x Hispanic$_{i,c,t}$	-0.0259	-0.0053	-6.9868			
	(-1.32)	(-1.40)	(-1.22)			
Opioid Death Rate$_{c,t-1}$ x Other$_{i,c,t}$	-0.0124	0.0074	13.9453			
	(-0.36)	(1.11)	(1.38)			
High Opioid Death Rate$_{c,t-1}$ x Black$_{i,c,t}$				1.6060***	-0.2992***	-350.4262**
				(3.08)	(-3.01)	(-2.32)
High Opioid Death Rate$_{c,t-1}$ x Hispanic$_{i,c,t}$				-0.5629	-0.0961	-127.482
				(-1.45)	(-1.29)	(-1.13)
High Opioid Death Rate$_{c,t-1}$ x Other$_{i,c,t}$				-0.1696	0.1553	302.4677
				(-0.21)	(1.01)	(1.3)
Opioid Death Rate$_{c,t-1}$	0.4823***	-0.0616***	-73.6077**			
	(4.30)	(-2.87)	(-2.26)			
High Opioid Death Rate$_{c,t-1}$				1.0878***	-0.1411***	-169.3513**
				(4.25)	(-2.89)	(-2.29)
Black$_{i,c,t}$	-0.5181*	0.1201**	145.4275*	-0.5337**	0.1189**	143.5116*
	(-1.81)	(2.19)	(1.75)	(-2.01)	(2.35)	(1.87)
Hispanic$_{i,c,t}$	0.4932***	-0.0009	5.3688	0.4526***	-0.0109	-7.9967
	(2.75)	(-0.03)	(0.10)	(3.07)	(-0.39)	(-0.19)
Other$_{i,c,t}$	0.288	-0.0702	-112.593	0.2283	-0.056	-90.9313
	(0.87)	(-1.11)	(-1.18)	(0.77)	(-0.99)	(-1.06)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.316	0.156	0.082	0.311	0.153	0.079
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 8: Heterogeneous Effects for Minority, Low Income, and Young Consumers (cont.)

This table examines how the effects of opioid crisis intensity on bank credit card terms differ by consumer race, income, and age using interactions of consumer race/minority and opioid intensity in Panels A and B, and interactions of consumer low income ($\leq$\$30k) and young ($\leq$25 yrs) with opioid intensity in Panels C and D. In all cases, we report IV 2SLS regression estimates (equations (3) and (4)) using "Mkt Doctors/1000Pop" as an instrument for opioid crisis intensity. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel C: Low Income ($\leq$\$30k) Consumers

Dependent Variables:	Rate Spread	Ln(Limit)	Limit (\$)	Rate Spread	Ln(Limit)	Limit (\$)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$ x Low Income$_{i,c,t-1}$	0.0445***	-0.0062**	-4.2787			
	(2.78)	(-2.03)	(-0.92)			
High Opioid Death Rate$_{c,t-1}$ x Low Income$_{i,c,t-1}$				1.2101***	-0.1701**	-130.927
				(3.30)	(-2.43)	(-1.24)
Opioid Death Rate$_{c,t-1}$	0.4627***	-0.0673***	-83.8340***			
	(4.26)	(-3.24)	(-2.66)			
High Opioid Death Rate$_{c,t-1}$				1.0367***	-0.1507***	-187.9986***
				(4.22)	(-3.22)	(-2.65)
Low Income$_{i,c,t-1}$	-0.2939	0.0424	9.2884	-0.3751*	0.0542	24.324
	(-1.48)	(1.11)	(0.16)	(-1.93)	(1.46)	(0.43)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.314	0.153	0.081	0.305	0.148	0.078
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Panel D: Young ($\leq$25 yrs) Consumers

Dependent Variables:	Rate Spread	Ln(Limit)	Limit (\$)	Rate Spread	Ln(Limit)	Limit (\$)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$ x Young$_{i,c,t}$	0.0627*	-0.0072	-7.7118			
	(1.72)	(-1.03)	(-0.73)			
High Opioid Death Rate$_{c,t-1}$ x Young$_{i,c,t}$				1.8895**	-0.2259	-247.88
				(2.18)	(-1.37)	(-0.99)
Opioid Death Rate$_{c,t-1}$	0.5106***	-0.0705***	-82.6125***			
	(4.85)	(-3.50)	(-2.71)			
High Opioid Death Rate$_{c,t-1}$				1.1798***	-0.1623***	-189.9956***
				(4.93)	(-3.56)	(-2.75)
Young$_{i,c,t}$	0.5136	-0.0845	-80.6218	0.2715	-0.0521	-43.159
	(1.21)	(-1.04)	(-0.65)	(0.60)	(-0.60)	(-0.33)
Fit statistics						
Observations	197,371	197,371	197,371	197,371	197,371	197,371
Adj. R^2	0.315	0.157	0.083	0.306	0.152	0.08
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓

Table 9: Credit Card Rewards and Likelihood of Credit Card Offer

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and two additional bank credit card elements: rewards/promotions and likelihood of a credit card offer. Panel A reports second-stage IV estimates for credit card rewards/promotions from offer-level data, while Panel B reports estimates for the likelihood credit card offer using an extended sample covering all mailings of consumers with and without credit card offers in each month. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions in Panel A include *State* × *Year-Month, Lender* × *Year-Month, Lender* × *State, Lender, State,* and *Year-Month* fixed effects. Panel B Panel A includes *State* × *Year-Month, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign (State) and Year-Month in Panels A(B) and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV 2LS for Credit Card Rewards/Promotions

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Rewards/ Promotions	Rewards/ Promotions
Model:	(1)	(2)	(3)	(4)
Mkt Doctors/1000Pop$_{c,t-1}$	1.0349***	0.4511***		
	(21.65)	(12.85)		
Opioid Death Rate$_{c,t-1}$			-0.0173**	
			(-2.38)	
High Opioid Death Rate$_{c,t-1}$				-0.0396**
				(-2.37)
Fit statistics				
Observations	197,371	197,371	197,371	197,371
Adj. R^2	0.559	0.421	0.057	0.055
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Panel B: IV 2SLS for Likelihood of Credit Card Offer

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Credit Card Offer	Credit Card Offer
Model:	(1)	(2)	(3)	(4)
Mkt Doctors/1000Pop$_{c,t-1}$	11.1551***	0.5140**		
	(3.01)	(2.42)		
Opioid Death Rate$_{c,t-1}$			-0.0046***	
			(4.70)	
High Opioid Death Rate$_{c,t-1}$				-0.1005***
				(-4.70)
Fit statistics				
Observations	392,101	392,101	392,101	392,101
Adj. R^2	0.547	0.403	0.115	0.112
Fixed effects				
State × Year-Month	✓	✓	✓	✓
State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Table 10: Opioid Supply and Opioid Demand Laws

This table conducts a horse race to examine the impact of 6 different opioid state laws in the US on opioid prescription and deaths in Panel A (using a county-year level sample), and on consumer credit supply in Panel B (using our main offer-level sample). We cover three opioid-supply oriented laws (Opioid Limiting Law, PDMP Law, Triplicate Prescription Law) and three demand/user oriented laws (Naloxone Law, Good Samaritan Law, Medical Marijuana Permitting Law). All laws are time variant, except for Triplicate Prescription Law and Medical Marijuana Permitting Law, which are time-invariant over our sample period. Panel B reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" as an instrument for opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*), based on data from the CDC). All variables used in Panel B are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. In Panel A using a county-year sample, regressions include *County, State,* and *Year* fixed effects in columns 1-4 and Year fixed effects in columns 5-8. In Panel B, using our offer-level sample, all regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Variables are defined in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Effects of *"Opioid Supply and Opioid Demand Laws"* on Opioid Prescriptions and Deaths

Dependent Variables:	Opioid Prescription Rate	Opioid Death Rate	Opioid Prescription Death Rate	Opioid Illicit Death Rate	Opioid Prescription Rate	Opioid Death Rate	Opioid Prescription Death Rate	Opioid Illicit Death Rate
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opioid Supply Laws:								
Opioid Limiting Law$_s$ x Post$_{s,t}$	-0.0297***	0.2317***	-0.0400***	0.2941***				
	[-5.10]	[10.78]	[-2.84]	[16.39]				
Opioid PDMP Law$_s$ x Post$_{s,t}$	-0.0757***	0.1754***	-0.0785***	0.3011***				
	[-17.04]	[7.73]	[-4.54]	[18.49]				
Triplicate Prescription Law$_s$					-0.1215***	-0.3287***	-0.2054***	-0.1699***
					[-19.85]	[-25.37]	[-23.46]	[-17.62]
Opioid Demand Laws:								
Naloxone Law$_s$ x Post$_{s,t}$	0.001	0.017	0.0213	[0.007]				
	[0.27]	[0.95]	[1.59]	[-0.56]				
Samaritan Law$_s$ x Post$_{s,t}$	-0.0128***	0.0360**	0.0026	0.0334***				
	[-3.64]	[2.12]	[0.21]	[2.66]				
Medical Marijuana Permitting Law$_s$					-0.0701***	0.0554***	-0.0450***	0.1106***
					[-13.81]	[4.23]	[-5.21]	[11.16]
Fit statistics								
Observations	27,955	30,563	30,563	30,563	28,052	30,565	30,565	30,565
Adj. R^2	0.866	0.488	0.394	0.474	0.295	0.136	0.063	0.193
Fixed effects								
County, State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: Effects of Opioid Laws on Credit Card Terms

Panel B1: Time-Variant *"Opioid Supply and Opioid User Laws"*

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)
Opioid Supply Laws:				
Opioid Limiting Law$_s$ x Post$_{s,t}$	-0.2280***	0.0198*	-0.1073***	0.0046
	(-4.16)	(1.89)	(-3.28)	(0.74)
Opioid PDMP Law$_s$ x Post$_{s,t}$	-0.2263***	0.0379***	-0.1661***	0.0304***
	(-3.90)	(3.42)	(-3.42)	(3.29)
Opioid Demand Laws:				
Naloxone Law$_s$ x Post$_{s,t}$	0.0772**	0.0084	-0.0192	0.0204***
	(2.47)	(1.40)	(-0.49)	(2.76)
Samaritan Law$_s$ x Post$_{s,t}$	0.0538*	-0.0108*	0.0938***	-0.0158**
	(1.67)	(-1.74)	(2.66)	(-2.35)
Opioid Crisis Variables:				
Opioid Death Rate$_{c,t-1}$	0.4783***	-0.0599***		
	(3.99)	(-2.62)		
High Opioid Death Rate$_{c,t-1}$			1.0462***	-0.1310***
			(3.98)	(-2.62)
Fit statistics				
Observations	197,448	197,448	197,448	197,448
Adj. R^2	0.322	0.161	0.318	0.160
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓

Table 10: Opioid Supply and Opioid User Laws (cont.)

This table conducts a horse race to examine the impact of 6 different opioid state laws in the US on opioid prescription and deaths in Panel A (using a county-year level sample), and on consumer credit supply in Panel B (using our main offer-level sample). We cover three opioid-supply oriented laws (Opioid Limiting Law, PDMP Law, Triplicate Prescription Law) and three demand/user oriented laws (Naloxone Law, Good Samaritan Law, Medical Marijuana Permitting Law). All laws are time variant, except for Triplicate Prescription Law and Medical Marijuana Permitting Law, which are time-invariant over our sample period. Panel B reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" as an instrument for opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*), based on data from the CDC). All variables used in Panel B are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. In Panel A using a county-year sample, regressions include *County, State,* and *Year* fixed effects in columns 1-4 and Year fixed effects in columns 5-8. In Panel B, using our offer-level sample, all regressions include *State* × *Year-Month, Lender* × *Year-Month, Lender* × *State, Lender, State,* and *Year-Month* fixed effects. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Variables are defined in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel B2: *Opioid Supply Law*: "Triplicate Prescription Law" (Time-Invariant)

	Triplicate Prescription Law?							
	Yes		No		Yes		No	
Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opioid Death Rate$_{c,t-1}$	0.2384	-0.0611**	0.6990***	-0.0814***				
	(1.56)	(-2.05)	(4.48)	(-2.76)				
High Opioid Death Rate$_{c,t-1}$					0.4216	-0.1080**	1.9144***	-0.2229***
					(1.56)	(-2.05)	(4.41)	(-2.74)
Fit statistics								
Observations	58,762	58,762	138,352	138,352	58,762	58,762	138,352	138,352
Adj. R^2	0.321	0.161	0.308	0.155	0.320	0.160	0.286	0.146
Fixed effects								
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓	✓	✓

Panel B3: *Opioid Demand Law*: "Medical Marijuana Permitting Law" (Time-Invariant)

	Medical Marijuana Permitting Law?							
	Yes		No		Yes		No	
Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Opioid Death Rate$_{c,t-1}$	0.4240***	-0.0707***	0.3554	-0.0242				
	(4.77)	(-4.14)	(0.76)	(-0.27)				
High Opioid Death Rate$_{c,t-1}$					1.1621***	-0.1937***	0.5663	-0.0385
					(4.74)	(-4.13)	(0.76)	(-0.27)
Fit statistics								
Observations	133,304	133,304	63,829	63,829	133,304	133,304	63,829	63,829
Adj. R^2	0.311	0.153	0.347	0.176	0.302	0.147	0.347	0.176
Fixed effects								
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓	✓	✓

Table 11: Possible Underlying Mechanisms using Additional Datasets

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity and consumer credit card behavior and/or quality in Panel A and bank credit card and unsecured consumer portfolio quality in Panel B. Opioid crisis intensity is measured as *Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC. Consumer credit card behavior and/or quality is measured several ways as: Ln(Avg Days Past Due), Avg Loan Probability of Default (PD), Ln(Avg Payment), and Avg Updated Consumer Credit Score). Bank credit card portfolio quality is measured as the nonperforming loans ratios of NPL Credit Cards and NPL Unsecured Consumer Credit. The analysis in Panel A uses aggregated bank-county-year-month data from the supervisory FR Y-14M credit card dataset based on a 0.1% random sample for existing consumer accounts (loan age $\geq$ 12 months). Analysis in Panel B uses public bank-quarter data from the FFIEC Call Reports. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by County and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV 2SLS Effects: Effects on Credit Card Consumer Credit Behavior and/or Quality

Dependent Variables:	Opioid Death Rate	High Opioid Death Rate	Ln(Avg Days Past Due)	Avg Prob Default (PD)	Ln(Avg Payment)	Avg Credit Score	Ln(Avg Days Past Due)	Avg Prob Default (PD)	Ln(Avg Payment)	Avg Credit Score
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mkt Doctors/1000Pop$_{c,t-1}$	0.5578***	0.0904***								
	(61.99)	(22.65)								
Opioid Death Rate$_{c,t-1}$			0.0860***	0.0020***	-0.1391***	-2.6294***				
			(8.10)	(2.61)	(-9.46)	(-4.03)				
High Opioid Death Rate$_{c,t-1}$							0.5305***	0.0124***	-0.8584***	-16.2190***
							(7.69)	(2.59)	(-8.82)	(-3.97)
Fit statistics										
Observations	1,009,322	1,009,322	1,009,313	694,562	1,009,138	1,009,322	1,009,313	694,562	1,009,138	1,009,322
Adj. R^2	0.050	0.050	0.088	0.002	0.090	0.017	0.002	0.001	0.072	0.009
Fixed effects										
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: IV 2SLS Effects on Bank Credit Card Portfolio Quality

Dependent Variables:	NPL Credit Cards	NPL Unsecured Consumer Credit	NPL Credit Cards	NPL Unsecured Consumer Credit
Model:	(1)	(2)	(3)	(4)
Opioid Death Rate$_{b,t-1}$	1.3449**	1.5780**		
	(2.20)	(2.35)		
High Opioid Death Rate$_{b,t-1}$			1.2325***	1.7757***
			(3.71)	(4.07)
Fit statistics				
Observations	16,866	16,866	16,866	16,866
Adj. R^2	0.750	0.750	0.708	0.709
Fixed effects				
Lender, Year-Quarter	✓	✓	✓	✓
Lender & County controls	✓	✓	✓	✓

Table 12: Possible Macro Real Effects of The Opioid Crisis - Consumer Spending

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity and consumer credit card terms to consumers in Panel A, and consumer credit card spending in Panel B. Opioid crisis intensity is measured as *Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC. Credit card terms are measured several ways as: Avg Cycle APR, Ln(Avg Limit), Limit/Pop, and Pct Cards with Rewards. Consumer spending is measured several ways as: Ln(Avg Purchase), Total Purchase/Pop, and Purchase/Limit. All analyses in this table use aggregated bank-county-year-month data from the supervisory FR Y-14M credit card dataset based on a 0.1% random sample for existing consumer accounts (loan age $\geq$ 12 months). Analysis in Panel B uses public bank-quarter data from the FFIEC Call Reports. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by County and Year-Month in Panel A and clustered by Lender in Panel B, and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV 2SLS Effects: Reconfirm Results for Credit Card Terms

Dependent Variables:	Avg Cycle APR	Limit /Pop	Pct Cards w/ Rewards	Avg Cycle APR	Limit Pop	Pct Cards w/ Rewards
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$	0.3433***	-0.0070***	-0.0178***			
	(5.30)	(-6.90)	(-4.12)			
High Opioid Death Rate$_{c,t-1}$				2.1138***	-0.0431***	-0.1099***
				(5.17)	(-6.65)	(-4.06)
Fit statistics						
Observations	1,008,285	1,008,631	1,009,322	1,008,285	1,008,631	1,009,322
Adj. R^2	0.001	0.021	0.002	0.001	0.006	0.001
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓

Panel B: IV 2SLS Effects on Consumer Spending

Dependent Variables:	Total Purchase /Pop	Total Purchase /Limit	Ln (Avg Purchase)	Total Purchase /Pop	Total Purchase /Limit	Ln (Avg Purchase)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$	-0.0070***	-0.0149***	-0.1422**			
	(-6.90)	(-6.14)	(-3.58)			
High Opioid Death Rate$_{c,t-1}$				-0.0431***	-0.0922***	-0.8818**
				(-6.65)	(-5.95)	(-3.54)
Fit statistics						
Observations	1,008,631	1,008,631	1,004,460	1,008,631	1,008,631	1,004,460
Adj. R^2	0.021	0.001	0.112	0.010	0.001	0.098
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓

Internet Appendix: Supplementary Materials and Analyses

Table A1: Variable Definitions and Sources

This table provides definitions and data sources for the variables used in the analysis. Panel A shows variables used in all analyses, including opioid intensity measures from the Centers for Disease Control and Prevention (briefly noted in tables and below as CDC), instrumental variables from several sources, and county characteristics from several sources noted below. Panel B shows additional variables from the anonymized FRBNY Consumer Credit Panel/Equifax dataset (FRBNY CCP). Panel C shows additional variables from the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File (briefly noted in tables and below as Mintel/TransUnion Match File). Consumer demographic attributes are from the Mintel/TransUnion Match File. Panel D shows additional variables from the public bank FFIEC Call Reports data and FDIC Summary of Deposits (SoD). Panel E provides summary statistics for the Call Reports analysis.

Variable	Definition	Source
Key Independent Variables		
Opioid Death Rate	Opioid deaths per 10K SEER population in the county, lagged one year. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	CDC/NCHS, National Center for Health Statistics
High Opioid Death Rate	Indicator for high total opioid death rate in the county (in the upper 50th percentile of the distribution) lagged 1 year. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	CDC/NCHS, National Center for Health Statistics
Prescription Opioid Death Rate	Opioid deaths due to prescription opioids per 10K SEER population in the county, lagged 1 year.	CDC/NCHS, National Center for Health Statistics
Illicit Opioid Death Rate	Opioid deaths due to illicit opioids per 10K SEER population in the county, lagged 1 year.	CDC/NCHS, National Center for Health Statistics
Opioid Prescription Rate	Opioid prescriptions per capita in the county, lagged one year. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	CDC/IQVIA Xponent
High Opioid Prescription Rate	Indicator for high prescription opioid death rate in the county (in the upper 50th percentile of the distribution) lagged 1 year. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	CDC/IQVIA Xponent
Instrumental Variables		
MKT Doctors/1000Pop	Number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	Hadland et al. (2019), Open Payments Database
High Purdue MKT (OxyContinGrowth '97-'02)	Indicator for counties in the upper 50th percentile of the distribution of the percentage change in the quantity of OxyContin distributed by Purdue Pharma between 1997 and 2002. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	DEA, Cornaggia et al. (2021)
Purdue MKT (OxyContin Growth '97-'02)	Percentage change in the quantity of OxyContin distributed by Purdue Pharma in the county between 1997 and 2002. Bank-level analysis uses a weighted measure using the fraction of bank branches in the county as a weight.	DEA, Cornaggia et al. (2021)
County Characteristics		
Ln(County Income)	Natural log of county income, lagged 1 year.	Bureau of Economic Analysis
County Unemployment Rate	County unemployment rate lagged 1 quarter.	Haver Analytics/BLS
County Bank HHI	Bank HHI of deposits at the county level.	FDIC Summary of Deposits (SoD)
County Population Density	County population density.	U.S. Census Bureau
County Race HHI	County HHI for population races.	U.S. Census American Community Surveys
County % Male	County percent of male population.	U.S. Census American Community Surveys
County % Age_25_44	County percent population ages 25-44.	U.S. Census American Community Surveys
County % Age_45_64	County percent population ages 45-64.	U.S. Census American Community Surveys
County % Age_65plus	County percent population ages 65 and above.	U.S. Census American Community Surveys
County % High Education ($\geq$ College)	County percent of population with higher education.	U.S. Census American Community Surveys
County Inequality: Gini Coefficient	County inequality proxied by the Gini Coefficient.	U.S. Census American Community Surveys

Table A1: Variable Definitions and Sources (cont.)

Variable	Definition	Source
Key Dependent Variables		
Rate Spread	The APR Spread over the one-month Treasury bonds.	Mintel/TransUnion Match File
Ln(Limit)	Natural log of credit card limit in the offer.	Mintel/TransUnion Match File
Limit ($)	Credit card limit in the offer in dollars.	Mintel/TransUnion Match File
Card Offer	Dummy for a credit card offer, and zero otherwise.	Mintel/TransUnion Match File
Consumer Characteristics		
Consumer Credit Score	Credit score, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_Less580	Credit score range: less than 580 or 300-580, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_580_660	Credit score range: 580-660, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_660_720	Credit score range: 660-720, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_720_800	Credit score range: 720-800, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_800plus	Credit score range: greater or equal to 800.	Mintel/TransUnion Match File
Deep_Delinq	Indicator for consumers with past deep delinquency 90 days past due or more on their loans, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Recent_Delinq	Indicator for consumers with recent delinquency 90 days past due or more on their loans, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Other_Derogatory	Indicator for consumers with past derogatory filings such as foreclosure, collections etc., as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Bankruptcy_Filer	Indicator for consumers with past bankruptcy filings, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
High_Util ($\geq$80%)	Indicator for consumers with high credit card utilization in the past (80% or more), as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Ln(1+ No Credit Inquiries)	Natural log of one plus number of credit inquiries by the consumer, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Has_Prior_Cards	Indicator for consumers who have prior credit cards, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Consumer Age	Consumer age.	Mintel/TransUnion Match File
Age_Less25	Consumer age below 25.	Mintel/TransUnion Match File
Age_25to44	Consumer age range 25 to 44.	Mintel/TransUnion Match File
Age_45to64	Consumer age range 45 to 64.	Mintel/TransUnion Match File
Age_65plus	Consumer age 65 and above.	Mintel/TransUnion Match File
Married	Indicator for married consumers, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
No_Kids	Indicator if the consumer has no kids, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
White	Indicator for White or non-minority consumers.	Mintel/TransUnion Match File
Miss_Race	Indicator for missing/unreported race.	Mintel/TransUnion Match File
Educ: Some_College	Indicator for education: some college.	Mintel/TransUnion Match File
Educ: College	Indicator for education: college.	Mintel/TransUnion Match File
Educ: Post_College	Indicator for education: post-college.	Mintel/TransUnion Match File
Miss Educ	Indicator for missing/unreported education.	Mintel/TransUnion Match File
Homeowner	Indicator for homeowners, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Ln(Consumer Income)	Natural log of consumer annual income, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File

Table A2: Additional Tests to Support the Main Findings

This table reports robustness checks for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports results when additionally including more county-level controls; Panel B reports results when using multiple death causes rather than underlying death cause for construction of our opioid intensity death measures; Panel C reports results using OLS estimates instead of IV estimates; Panel D reports results when excluding counties with ”zero deaths”; and Panel D reports results when excluding the state of Florida. We report in all cases other than Panel C regression estimates from IV 2SLS regressions (equations (3) and (4)) using the ”Mkt Doctors/1000Pop” as an instrument for opioid intensity. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as ”banks” in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month, Lender × Year-Month, Lender × State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV 2SLS with Even More County-Level Controls

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)
Opioid Death Rate$_{c,t-1}$	0.4728***	-0.0648***		
	(4.27)	(-3.06)		
High Opioid Death Rate$_{c,t-1}$			1.1738***	-0.1610***
			(4.25)	(-3.05)
Additional Controls				
County Labor Participation Rate$_{c,t-1}$	0.5144	-0.4368***	0.4620	-0.4296***
	(1.15)	(-5.10)	(1.04)	(-5.04)
County Avg Credit Score$_{c,t-1}$	-0.0001	0.0038**	-0.0001	
	(2.28)	(-0.44)	(2.29)	(-0.46)
County Air Pollution$_{c,t-1}$	-0.0510***	0.0041*	-0.0555***	0.0047*
	(-4.23)	(1.76)	(-4.31)	(1.90)
County Δ HPI$_{c,t-1}$	-0.0078**	0.0021***	-0.0076**	0.0020***
	(-2.14)	(2.97)	(-2.08)	(2.92)
County % School Dropouts$_{c,t-1}$	-1.7398***	-0.0433	-0.9908*	-0.1460
	(-3.60)	(-0.47)	(-1.81)	(-1.40)
County % Religious Pop$_{c,t-1}$	-0.0011	0.0365*	-0.1161	0.0523***
	(-0.01)	(1.70)	(-1.18)	(2.79)
County Politics$_{c,t-1}$	0.0039	-0.0004	0.0011	0.0000
	(0.29)	(-0.15)	(0.08)	(0.00)
County Poverty Rate$_{c,t-1}$	0.5590	-0.0576	1.5609***	-0.1950*
	(0.88)	(-0.47)	(2.65)	(-1.73)
County % Poor Health Pop$_{c,t-1}$	-0.0087*	0.0018**	-0.0151***	0.0026***
	(-1.95)	(2.06)	(-2.98)	(2.73)
Fit statistics				
Observations	195,004	195,004	195,004	195,004
Adj. R^2	0.319	0.158	0.312	0.154
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Table A2: Additional Tests to Support the Main Findings (cont.)

This table reports robustness checks for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports results when additionally including more county-level controls; Panel B reports results when using multiple death causes rather than underlying death cause for construction of our opioid intensity death measures; Panel C reports results using OLS estimates instead of IV estimates; Panel D reports results when excluding counties with "zero deaths"; and Panel D reports results when excluding the state of Florida. We report in all cases other than Panel C regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" as an instrument for opioid intensity. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month*, *Lender × Year-Month*, *Lender × State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel B: IV 2SLS - Alternative Opioid Death Rate based on Multiple Death Causes

Dependent Variables: Model:	Rate Spread (1)	Ln(Limit) (2)	Rate Spread (3)	Ln(Limit) (4)
Opioid Death Rate$_{c,t-1}$	0.5069***	-0.0703***		
	(4.94)	(-3.58)		
High Opioid Death Rate$_{c,t-1}$			1.2413***	-0.1722***
			(4.91)	(-3.57)
Fit statistics				
Observations	197,398	197,398	197,398	197,398
Adj. R^2	0.317	0.157	0.310	0.154
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Panel C: Results using OLS Method

Dependent Variables: Model:	Rate Spread (1)	Rate Spread (2)	Rate Spread (3)	Rate Spread (4)	Ln(Limit) (5)	Ln(Limit) (6)	Ln(Limit) (7)	Ln(Limit) (8)
Opioid Death Rate$_{c,t-1}$	0.0216**				-0.0026			
	(2.27)				(-1.24)			
High Opioid Death Rate$_{c,t-1}$		0.0184				-0.0076**		
		(1.28)				(-2.28)		
Opioid Illicit Death Rate$_{c,t-1}$			0.0263**				-0.0045*	
			(2.34)				(-1.88)	
High Opioid Illicit Death Rate$_{c,t-1}$				0.0298*				-0.0088**
				(1.84)				(-2.28)
Fit statistics								
Observations	370802	370802	370802	370802	370802	370802	370802	370802
Adj. R^2	0.662	0.662	0.662	0.662	0.428	0.428	0.428	0.428
Fixed effects								
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓	✓	✓	✓	✓

Table A2: Additional Tests to Support the Main Findings (cont.)

This table reports robustness checks for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports results when additionally including more county-level controls; Panel B reports results when using multiple death causes rather than underlying death cause for construction of our opioid intensity death measures; Panel C reports results using OLS estimates instead of IV estimates; Panel D reports results when excluding counties with "zero deaths"; and Panel D reports results when excluding the state of Florida. We report in all cases other than Panel C regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" as an instrument for opioid intensity. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as "banks" in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month, Lender × Year-Month, Lender × State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel C: Results using OLS Method (cont.)

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)
Opioid Prescription Rate$_{c,t-1}$	0.1934***	-0.0227***		
	(5.53)	(-3.36)		
High Opioid Prescription Rate$_{c,t-1}$			0.1142***	-0.0130***
			(6.71)	(-3.45)
Fit statistics				
Observations	369,263	369,263	369,263	369,263
Adj. R^2	0.662	0.428	0.662	0.428
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Panel D: IV 2SLS Excluding Counties with "Zero Deaths"

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)
Opioid Death Rate$_{c,t-1}$	0.4682***	-0.0718***		
	(4.42)	(-3.54)		
High Opioid Death Rate$_{c,t-1}$			1.0678***	-0.1639***
			(4.40)	(-3.54)
Fit statistics				
Observations	194,293	194,293	194,293	194,293
Adj. R^2	0.317	0.157	0.312	0.154
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Table A2: Additional Tests to Support the Main Findings (cont.)

This table reports robustness checks for explaining the relationship between opioid crisis intensity (*Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC) and bank credit card terms: rate spread and credit card limit. Panel A reports results when additionally including more county-level controls; Panel B reports results when using multiple death causes rather than underlying death cause for construction of our opioid intensity death measures; Panel C reports results using OLS estimates instead of IV estimates; Panel D reports results when excluding counties with ”zero deaths”; and Panel D reports results when excluding the state of Florida. We report in all cases other than Panel C regression estimates from IV 2SLS regressions (equations (3) and (4)) using the ”Mkt Doctors/1000Pop” as an instrument for opioid intensity. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card mail offers. The data are focused on lenders identified as ”banks” in the Mintel/TransUnion Match File. Demographic attributes are from Mintel. Consumer controls include: credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure and collections, past bankruptcy filings, past high utilization ($\geq$ 80%), number of credit inquiries, past credit cards, consumer age ranges, married, indicator for no kids, White, education indicators, homeowner, and consumer income. County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State × Year-Month, Lender × Year-Month, Lender × State, Lender, State,* and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by Marketing Campaign and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel E: IV 2SLS Excluding Florida

Dependent Variables:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)
Model:	(1)	(2)	(3)	(4)
Opioid Death Rate$_{c,t-1}$	0.7523***	-0.1003***		
	(5.79)	(-4.04)		
High Opioid Death Rate$_{c,t-1}$			1.8456***	-0.2461***
			(5.72)	(-4.02)
Fit statistics				
Observations	182,900	182,900	182,900	182,900
Adj. R^2	0.308	0.153	0.293	0.146
Fixed effects				
State × Year-Month	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓
Consumer & County controls	✓	✓	✓	✓

Table A3: Extra Results for Mechanisms, Credit, & Spending (County-Year-Month)

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity and consumer credit card behavior and/or quality in Panel A, bank credit card terms to consumers in Panel B, and consumer credit card spending in Panel C. Opioid crisis intensity is measured as *Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC. Consumer credit card behavior and/or quality is measured several ways as: Ln(Avg Days Past Due), Avg Loan Probability of Default (PD), Ln(Avg Payment), and Avg Updated Consumer Credit Score). Credit terms are measured several ways as: Avg Cycle APR, Ln(Avg Limit), Limit/Pop, and Pct Rewards (percent of accounts with rewards). Consumer spending is measured several ways as: Ln(Avg Purchase), Total Purchase/Pop, Purchase/Limit, Avg Purchase ($). All these analyses use aggregated bank-county-year-month data from the supervisory FR Y-14M credit card dataset based on a 0.1% random sample for existing consumer accounts (loan age $\geq$ 12 months). County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by County and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV 2SLS Effects: Effects on Credit Card Consumer Credit Behavior and/or Quality

Dependent Variables: Model:	Opioid Death Rate (1)	Ln(Avg Days Past Due) (2)	Avg Prob Default (PD) (3)	Ln(Avg Payment) (4)	Avg Credit Score (5)	High Opioid Death Rate (6)	Ln(Avg Days Past Due) (7)	Avg Prob Default (PD) (8)	Ln(Avg Payment) (9)	Avg Credit Score (10)
Mkt Doctors/1000Pop$_{c,t-1}$	0.4388***					0.0669***				
	(17.92)					(6.04)				
Opioid Death Rate$_{c,t-1}$		0.2367***	0.0034***	-0.6148***	-7.1076***					
		(5.84)	(2.40)	(-11.01)	(-5.33)					
High Opioid Death Rate$_{c,t-1}$							1.5526***	0.0233***	-3.6161***	-46.6208***
							(4.32)	(2.23)	(-6.11)	(-4.12)
Fit statistics										
Observations	119,482	119,482	119,482	119,096	119,096	119,482	118,823	118,823	119,482	119,482
Adj. R^2	0.048	0.019	0.006	0.060	0.080	0.052	0.004	0.001	0.010	0.020
Fixed effects										
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: IV 2SLS Effects: Reconfirm Results for Credit Card Terms

Dependent Variables: Model:	Avg Cycle APR (1)	Ln(Avg Limit) (2)	Limit /Pop (3)	Pct Cards w/ Rewards (4)	Avg Cycle APR (5)	Ln(Avg Limit) (6)	Limit /Pop (7)	Pct Cards w/Rewards (8)
Opioid Death Rate$_{c,t-1}$	0.4674***	-0.2280***	-0.1244***	-0.0913***				
	(4.81)	(-10.87)	(-10.93)	(-9.76)				
High Opioid Death Rate$_{c,t-1}$					3.0659***	-1.4955***	-0.8162***	-0.5992***
					(3.85)	(-5.54)	(-5.56)	(-5.37)
Fit statistics								
Observations	119,482	119,482	119,482	119,482	119,482	119,482	119,482	119,482
Adj. R^2	0.004	0.040	0.113	0.009	0.001	0.004	0.030	0.001
State × Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
State, Year-Month	✓	✓	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓	✓	✓

Table A3: Extra Results on Mechanisms, Credit, & Spending (County-Year-Month) (cont.)

This table reports regression estimates from IV 2SLS regressions (equations (3) and (4)) using the "Mkt Doctors/1000Pop" instrument for explaining the relationship between opioid crisis intensity and consumer credit card behavior and/or quality in Panel A, bank credit card terms to consumers in Panel B, and consumer credit card spending in Panel C. Opioid crisis intensity is measured as *Opioid Death Rate* and *High Opioid Death Rate*, based on data from the CDC. Consumer credit card behavior and/or quality is measured several ways as: Ln(Avg Days Past Due), Avg Loan Probability of Default (PD), Ln(Avg Payment), and Avg Updated Consumer Credit Score). Credit terms are measured several ways as: Avg Cycle APR, Ln(Avg Limit), Limit/Pop, and Pct Rewards (percent of accounts with rewards). Consumer spending is measured several ways as: Ln(Avg Purchase), Total Purchase/Pop, Purchase/Limit, Avg Purchase ($). All these analyses use aggregated bank-county-year-month data from the supervisory FR Y-14M credit card dataset based on a 0.1% random sample for existing consumer accounts (loan age $\geq$ 12 months). County controls include: county income, unemployment rate, bank market concentration, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality. All regressions include *State* × *Year-Month*, *Lender* × *Year-Month*, *Lender* × *State*, *Lender*, *State*, and *Year-Month* fixed effects. Variables are defined in Appendix Table A1. Standard errors are double-clustered by County and Year-Month and t-statistics are reported in parentheses. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel C: IV 2SLS Effects on Consumer Spending

Dependent Variables:	Ln(Avg Purchase)	Total Purchase/Pop	Purchase /Limit	Ln(Avg Purchase)	Total Purchase/Pop	Purchase /Limit
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$	-0.5880***	-0.1244***	-0.0145***			
	(-9.96)	(-10.93)	(-6.57)			
High Opioid Death Rate$_{c,t-1}$				-3.1854	-0.8162***	-0.0950***
				(-6.36)	(-5.56)	(-4.60)
Fit statistics						
Observations	117,142	117,142	119,482	117,142	117,142	119,482
Adj. R^2	0.070	0.113	0.030	0.020	0.030	0.005
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
State, Year-Month	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓