The Opioid Epidemic and Consumer Finance: Quo Vadis?*

Sumit Agarwal† Wenli Li‡ Raluca Roman§ Nonna Sorokina¶

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Abstract

We investigate the spillover effects of the opioid epidemic on consumer finance: delinquency, bank consumer portfolio risk, and credit supply. Using multiple datasets and instruments capturing the pharmaceutical industry's opioid marketing intensity, we uncover unfavorable credit consequences for consumers living in high-exposed areas and banks operating there. Specifically, low-credit-score consumers in areas with high opioid exposure are more likely to default on their credit obligations. Banks with higher opioid-crisis-exposure incur larger consumer non-performing loans and charge-offs. In response, banks contract credit supply to consumers in these areas, applying stricter credit terms and reducing credit offers. This contraction disproportionately affects riskier, minority, and younger consumers.

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†National University of Singapore, ushakri@yahoo.com.
‡Federal Reserve Bank of Philadelphia, wenli.li@phil.frb.org.
§Federal Reserve Bank of Philadelphia, raluca.roman@phil.frb.org.
¶The Pennsylvania State University, sorokina@psu.edu.

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] From 1999 to 2019, more than half a million people died from overdoses involving either prescription or illicit opioids (Figure 1).[2] Another 2 million are suffering from opioid-related disorders.[3] What is more, the crisis has worsened over time, affecting an increasingly large spectrum of the population.[4] It is, thus, not surprising that there is now growing evidence linking opioid abuse to reduced labor force participation and increased unemployment.[5]

The adverse effect of the opioid crisis on the labor market has direct implications on consumer finances. Consumers who are either unemployed or underemployed are obviously at a higher risk of default. This is especially true for opioid abusers who use credit to sustain their opioid addiction. This higher default risk, in turn, poses significant yet elusive risks to lenders, particularly those operating in opioid-affected areas, due to the information asymmetry between lenders and borrowers. It is hard for lenders to directly detect individuals vulnerable to opioid addiction and/or those who would use the financing to sustain their addiction. As a result, lenders may shy away from harder-hit opioid areas to reduce exposure. Surprisingly, despite that the opioid crisis is a consumer health crisis, there is little evidence on how consumer markets are affected.

This paper provides, to our knowledge, the first comprehensive examination of the spillover effects of the opioid epidemic on the consumer credit markets. We address three key issues of consumer finance: consumer delinquency, bank consumer portfolio risk, and consumer credit supply. 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,

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

[2]The number of deceased from drug overdose surpassed deaths from auto accidents; see, among others, Quinones (2015), and the Centers for Disease Control and Prevention (CDC) 2021, https://www.cdc.gov/nchs/pressroom/nchs_press_releases_2021_20211117.htm.

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

[4]Relative to their respective population, opioid-related death rates have increased disproportionately among certain race, age, gender, and educational background groups, e.g., African American; prime-age workers, male in particular; and lower education strata (Figure 3).

[5]See Case and Deaton (2015), Krueger (2017), Harris, Kesslery, Murray and Glenn (2019), Currie, Jin and Schnell (2019), Aliprantis, Lee and Schweitzer (2020), and Ouimet, Simintzi and Ye (2020).

the Great Recession over 2007-2009, or the COVID-19 pandemic from 2020 onward. The 10 years covered in our analyses mark the second and the third waves of the opioid epidemic that recorded perhaps the most dangerous abuse using both prescription and more illicit opioids.[6,7]

For the analyses, we rely on two consumer-level and one bank-level datasets that inform us directly on consumers' credit performance and banks' portfolio credit risk and reactions of credit extension decisions to consumers. Specifically, we obtain individual credit performance variables for credit cards, auto loans, and mortgages from the anonymized credit bureau data from FRBNY Consumer Credit Panel/Equifax Data (FRBNY CCP). The bank portfolio variables covering several consumer loan types come from the regulatory Call Reports. The individual credit supply variables are constructed 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)).

While we cover several consumer products, we pay special attention to credit cards. The credit card market is large and important in the U.S., with over 175 million users that span over 80% of the consumers.[8] Credit cards are also significant determinants of bank risk, inducing high charge-off rates, partly due to their unsecured nature. Sudden and large rises in consumer defaults can deteriorate lenders' portfolio quality and contribute to financial crises. Moreover, credit cards, being unsecured, are more likely used by the opioid-impacted population.

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 both confidential opioid-related death rates and public opioid prescription rates collected from the CDC/National Center for Health Statistics (NCHS)[9] and the CDC/IQVIA Transactional Data Warehouse. Consumers'

[6]The three epidemic waves are shown in (Figure 1): 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 the synthetic opioid deaths, particularly from illicitly manufactured fentanyl.

[7]Results are robust to starting the sample earlier in 2007, when the mail-credit-offer data start reporting.

[8]See https://www.federalreserve.gov/publications/files/2018-report-economic-well-being-us-households-201905.pdf or https://files.consumerfinance.gov/f/documents/cfpb_consumer-credit-card-market-report_2021.pdf.

[9]National Center for Health Statistics, 2020. All-County Mortality Micro Data, as compiled from data pro-

drug abuse is then measured via the severity of the opioid crisis in their county of residence.

Our main findings are as follows. First, we find an increased likelihood for low-credit-score consumers to default on their credit cards, auto loans, and first mortgages, in counties with higher exposure to the opioid crisis. The impact is most significant for credit cards (one-standard deviation increase in the Opioid Death Rate suggests a 26%-40% increase in default probability). Second, banks with significant presence in the more exposed areas experience higher non-performing loans and higher charge-offs across the consumer lending sector. Lastly, credit card supply is greatly reduced in areas with higher exposure to the opioid crisis. Specifically, banks are much less likely (0.4%-7.0% decrease) to solicit consumers for credit cards in areas highly exposed to the opioid crisis. When they do, the terms of the credit offered are more stringent in the more exposed areas than in less affected areas, i.e., banks charge higher interest rates (0.6-1.1 percentage points higher) and offer much smaller credit limits (7.0%-15.0% decrease). Moreover, consumers with higher perceived credit risk (based on several measures including credit score, income, past delinquency, and derogatory filings, etc.), minorities, and younger consumers suffer disproportionately more from the tightening of bank credit supply. All in all, our analyses indicate that the opioid epidemic has unfavorable consequences for both consumers and banks.

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 (2018)). As a first step toward mitigating this and isolating the relations studied, we 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)).

vided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

Our first 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.[10] 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.

Our second instrument is based on the aggressive pre-sample marketing of OxyContin by Purdue Pharma between 1997 and 2002, after its market introduction in 1996. 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 has 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 robustness analyses to address identification and/or rule out alternative explanations: use many alternative definitions for the opioid crisis intensity; employ non-parametric propensity score matching where we match the counties' high-quartile opioid deaths and prescriptions counties to other non-treated counties by year and county characteristics; use contiguous counties only, different error clustering, different fixed effects, and 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; exclude the top and bottom 5% counties in terms of various characteristics; and conduct different

[10] To our knowledge, we are the first to introduce this instrument in the finance and economics literature.

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.

Finally, we analyze the effectiveness of recent laws and regulations about opioid abuse on consumer credit supply. 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 are the Opioid Prescription Limiting Law, the mandatory Prescription Drug Monitoring Program (PDMP) Law, the Naloxone Law, the Good Samaritan Law, the Triplicate Prescription Law, and the Medical Marijuana Permitting Law. We find some positive effects from some but not all of these laws in mitigating credit supply reduction by banks to consumers. Particularly, the Opioid Prescription Limiting Law, the mandatory PDMP, and the triplicate prescription law, appear to mitigate both opioid prescriptions and deaths as well as help revert some of the negative influences of the opioid epidemic on consumer credit supply. In contrast, the Naloxone Law, the Good Samaritan Law, and the Medical Marijuana Permitting Law appear to have little beneficial or even unfavorable effects on both opioid deaths and consumer credit supply. These results are illustrative of the different nature of the laws and are in line with some of the prior literature.

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

Several strands of literature inspired this research. First and foremost, there 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., Krueger (2017); Aliprantis, Lee and Schweitzer (2020); Harris, Kesslery, Murray and Glenn (2019); Ouimet, Simintzi and Ye (2020); 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 affected 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) see 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. Lastly, Jansen (2021) 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 comprehensive study of the credit consequences of the local opioid misuse on both consumer credit markets and banking. We include nationally representative data covering both subprime and prime borrowers, as well as a wide range of credit products. We evaluate consumer defaults, bank consumer portfolio risk, and consumer credit supply at the extensive and intensive margins.

Our work is also related to the literature studying credit consequences of natural disasters, such as hurricanes and wildfires. While the opioid epidemic is arguably a man-made disaster, its scale, concentration, and unexpected outbreaks in various areas resemble those of natural disasters. For consumer behavior, Gallagher and Hartley (2017) find surges in credit card delinquencies for most flooded residents after the hurricane struck, but the effects are small and short lived. Differentiating among consumers of different credit risk, several studies (e.g., Roth Tran and Wilson (2022); Gallaher, Billings and Ricketts (2022); Ratcliffe, Congdon, Teles, Stanczyk and Martín (2020)) find that only vulnerable individuals (subprime, low income) residing in disaster-struck areas suffer from credit score declines, higher mortgage and credit card delinquencies, and more often declare bankruptcy after disasters. Despite this, most studies suggest that banks generally increase lending to consumers and businesses, aiding them in the recovery efforts (Cortés and Strahan (2017); Koetter, Noth and Rehbein (2020)), but also protect themselves by securitizing high-risk loans (e.g., Ouazad and Kahn (2019)) and increasing their risk-based capital ratios (e.g., Lambert, Noth and Schüwer (2017)). The impacts on consumers and banks of the opioid epidemic are more complex than those of the natural disasters. In contrast to this literature, we find reduced rather than improved credit supply from banks due to the opioid crisis.

3 Opioid Abuse and Consumer Finance

We present 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.

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 medicine 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 only make the payment if the term in equation (1) is nonegative. Let ϕ denote the repayment decision, then we have $\phi = 1$, if $e * w - c \geq (1+r)b$, and $\phi = 0$ otherwise.[11]

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.

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

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 risk of defaulting on his loan obligations. 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.[12]

When we aggregate individual behavior to, say, the county level, the discussion above suggests 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 larger shares of non-performing loans and charge-offs.

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 the repayment probability 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

[12]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.

crisis, which, in our setup, can be captured by their repayment probability ϕ_1 and ϕ_2, and $\phi_1 \leq \phi_2$. 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 or will provided less credit than individual 2 despite the two looking 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. In reality, individuals' payment probabilities vary significantly and continuously even within a given location. 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 nicely into that in Stiglitz and Weiss (1981) (see *Alternative Sufficient Conditions for Credit Rationing*, pp. 399), where the expected revenue for lenders as a function of the credit terms is hump shaped due to information asymmetry with a continuum of types described by the payment probability here. Hence, credit rationing arises when information asymmetry becomes severe.

To summarize, our discussion indicates 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 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 loan performance, bank loan portfolio risk, and 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 performance and credit offers are at the individual/offer by year (year-month in the case of credit offers) 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 this 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.[13] 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.[14]

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. We use the opioid prescribing rates per capita, per county each year derived from the CDC public data.[15] The CDC's prescribing data originates 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 that opioid prescrip-

[13] 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.

[14] 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.

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

tions 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 first 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.[16]

Next, we 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 Performance and Credit Supply

4.2.1 Consumer Credit Performance

In our consumer credit performance, we use a 2.5% random sample of FRBNY CCP. The full FRBNY CCP is a nationally representative 5% random anonymous sample of all consumers with a Social Security number and a credit report drawn from the Equifax data. The dataset is structured as a quarterly panel, beginning in 1999, with snapshots of consumers' credit profiles captured at the end of each quarter. The credit panel captures almost completely the liability side of the consumers, including various debt holdings such as credit card debt, auto loans, and mortgages, and their respective performance status, current, 60 days past due, 90 days past due, etc. Credit scores and the subprime borrower designation are based on the Equifax Risk Score.

Of the random sample, we restrict attention to consumers between the ages of 18 and 85

[16] 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.

during the sample period of 2010-2019. As mentioned above, we chose 2010 as the beginning period whenever data availability allows to avoid confounding effects from the implementation of the CARD Act of 2009, the effects of the Global Financial Crisis (GFC) over 2007-2009, and the outbreak of the COVID-19 crisis in 2020.[17] To match the frequency of our other variables, particularly those related to the opioid crisis, we convert the data into annual frequency by keeping only the fourth quarter of each year.

4.2.2 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. As is the case for the credit performance, our analyses focus on the period 2010-2019.

4.2.3 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. Each month, Mintel selects about 4,000 consumers from a pool of 1 million consumers that Mintel acquired from a large survey service 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.

[17] The CARD Act made significant changes to credit card lending. For example, it puts regulatory limits on certain types of credit card fees and attempts to affect consumers' repayment behavior by requiring that monthly statements provide clear information on the costs of making only the minimum payment.

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.[18] 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 rate and limits for the offers, as well as non-missing consumer characteristics. The consumer credit score and score ranges used in this analysis are based on VantageScore 3.0 from the Mintel/TransUnion Match file. Data are from 2010 to 2019 as in our previous analyses.

4.2.4 County-Level Economic and Other Data

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 US Census Bureau American Community Surveys.

4.3 Descriptive Statistics

We provide definitions and data sources for the variables used in our analyses in the Appendix Table A1. Table 1 shows summary statistics of the key variables. The panels are organized according to the consumer credit outcomes that we study, and we focus on the period 2010-2019. Comparing the summary statistics at consumer level in Panels A and C, we see many similarities. However, consumers in the Mintel/TransUnion Match file are slightly older, have somewhat higher risk scores, and live in more affluent counties as evidenced by the county income.

5 Estimation Strategy

The unobservable nature of the consumer's opioid usage and health status presents the biggest challenge in our analyses. We, therefore, cannot directly test the impact of the opioid usage

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

on the individual's loan performance nor whether banks treat opioid users differently. Instead we ask whether individuals are more likely to default on their loan obligations if they reside in counties more heavily exposed to the opioid crisis, all else equal. We also subsequently ask whether banks with greater exposure to hard-hit areas incur higher consumer non-performing loans and higher charge-offs than other banks. Finally, we test whether banks are less likely to supply credit or apply more stringent terms to individuals living in more opioid-affected areas.

We measure a county's exposure to the opioid crisis by its opioid death and opioid prescription rates. For each credit outcome variable, we test whether opioid exposure has any explanatory power in addition to the control variables. In some analyses, we interact this exposure variable with a dummy for borrowers with low credit scores and test whether being in a region heavily affected by opioids impacts borrowers of different credit quality differently. Our primary measures of opioid exposure are continuous opioid death and prescription rates. Additionally, we classify a county as heavily exposed to the opioid crisis if its death rate or prescription rate ranks in the top 50th and top 25th percentile of the nation. The exposure measures are lagged by one year in all specifications.

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 causality 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 on the data availability). At the county level, we control for indicators of local economic conditions, including median income, income inequality (gini), and unemployment rate, as well as a variety of demographic characteristics represented by population density, race, gender, age, and educational attainment composition. We also control for bank's local market concentration (HHI of deposits), to account for potential uneven access to banking services and credit terms. Further, at the consumer level, we include an array of credit score-related variables, the consumer credit balances in different loan categories, presence of bankruptcy and other derogatory events in the credit history, race, education, family status, homeownership, and individual income, as well as measures of consumer age, a full palette depicting the borrower's financial and demographic profile. Finally, in the bank-level analyses, we control for major bank characteristics that define a bank's business model and performance, including tier 1 capital, liquidity, profitability, size, and age. Finally, we supplement the above-mentioned controls with 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:

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

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

As discussed in Section 4.1.2, the instrumental variables (IVs) we use are *MKTDoctors/1000Pop*, the number of doctors receiving opioid marketing payments from pharmaceutical companies per 1,000 population per year, which is time variant, covering 2013 onward, and *Purdue MKT (OxyContin Growth '97-'02)*, the growth rate in each county in the distribution of OxyContin pills between 1997 and 2002, 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 Performance

For consumer credit performance, we use the FRBNY CCP data where the unit of observation is consumer by year. We focus on the first default event, such as 90 days past due, and exclude the consumers from the analyses after the first default. Our estimation specification of consumer credit performance for a consumer i in local market (county) c at time t is as follows:

$$\begin{aligned} Y_{i,c,t} = \beta_0 + \beta_1 \widehat{OpioidExp}_{c,t-1} + [\beta_2 \widehat{OpioidExp}_{c,t-1} \times SubprimeConsumer_{i,c,t-1}] \\ + \beta_3 ConsumerControls_{i,t-1} + \beta_4 CountyControls_{c,t-1} + FE + \epsilon_{i,c,t}, \end{aligned} \tag{4}$$

where $Y_{i,c,t}$ indicates whether a consumer becomes delinquent on his credit card, auto loan, or first mortgage. *ConsumerControls* (lagged one period) captures individual-level observables such as age, Equifax Risk Score, and various credit balances. The variable *SubprimeConsumer* is a binary indicating whether the consumer has an Equifax Risk Score under 620. Additionally, we include other county by year information (also lagged one period), such as the county median income, unemployment rate, bank local market concentration proxied by the HHI of deposits, population density, percent of males, race concentration proxied by HHI of various races, percent of people in various age ranges, percent of people with higher education, and inequality proxied by the gini coefficient. Finally, we include state by year fixed effects to capture any other time-varying heterogeneity across local consumer markets, such as minimum wage, marginal tax rate, and government spending, among others.

5.2.2 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-quarter. The opioid crisis variables and the instruments here are weighted averages of a bank's exposure to the opioid death rates, prescription rates, or opioid marketing practices, across all counties in which the bank operates, using proportion of bank branches in the county as weights. Branch data is sourced from the FDIC Summary of Deposits. Alternatively, we also classify a bank as heavily exposed to the opioid crisis if its exposure to the death rate or prescription rate ranks in the top 50th and top 25th percentile in a particular time period. As in the previous models, we complement simple fixed-effects regressions with two-stage models with instrumental variables to strengthen our identification strategy. The first stage is modeled as per equation (3) above. Our outcome variables here are the bank's non-performing loans and net charge-off rates (charge-offs net of recoveries) across different categories of consumer loans. Specifically, our estimation specification of bank consumer loan portfolio performance for a bank j at time (year-quarter) t follows:

$$Y_{i,t} = \psi_0 + \psi_1 \widehat{OpioidExp}_{i,t-1} + \psi_2 BankControls_{i,t-1} + \psi_3 CountyControls_{c,t-1} \psi_4 FE + \zeta_{i,t}, \quad (5)$$

where $Y_{i,t}$ refers to proxies of bank portfolio performance. For example, *NPL Credit Cards* and *Net Charge-Offs Credit Cards* represent non-performing credit card loans to bank total assets and net charge-offs in credit cards to bank total assets, respectively. 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 such as the county median income, unemployment rate, bank competition in the county measured by the HHI of deposits, population density, percent of males, race concentration, percent of people in various age ranges, percent of people with higher education, and inequality, all aggregated to the bank level, based on the bank's branch share in each county of operation.

5.2.3 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:

$$\begin{aligned} Y_{i,c,t} = \delta_0 + \delta_1 \widehat{OpioidExp}_{c,t-1} + [\delta_2 \widehat{OpioidExp}_{c,t-1} \times SubprimeConsumer_{i,c,t}] \\ + \delta_3 ConsumerControls_{i,t-1} + \delta_4 CountyControls_{c,t-1} + FE + \xi_{i,c,t}, \end{aligned} \quad (6)$$

where $Y_{i,c,t}$ refers to one of the 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, or *Card Offer*, a binary indicating a consumer receiving a credit card offer.

Consumer-level controls (measured as of 2-3 months prior to the credit offer) include credit scores range binaries based on VantageScore 3.0, 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), as well as state, year-month, and lender by year-month fixed effects, whenever possible, to capture any lender-level heterogeneity, such as lender health and business models and practices over time.[19,20]

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 and by opioid prescription rates per 100 county population. Figure 1 presents the evolution of opioid-related deaths overall and when split by prescription and illicit drugs over time. This figure underlines three important waves in the crisis: the prescription opioid overdose wave from 1999 to 2009; the heroin (mostly illicit) overdose wave from 2010 to 2012; and the synthetic (illicitly manufactured) opioid overdose wave from 2013 onward. Figure 2

[19] Note that we are able to include lender by year-month fixed effects for 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.

[20] A unique strength of the Mintel/TranUnion Match data is that it reports 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.

depicts the time trend of both opioid death Rates and prescription rates.

As Figure 1 demonstrates, the overall opioid death rates have been moving up consistently over the years, tripling by the end of our sample period relative to earlier times. By category, we observe a steady increase in prescription death rates until 2011, after which the prescription death rates plateaued with only small declines or increases across some of the years, e.g., a small peak is observed over 2014-2017. The slowdown in prescription opioid deaths is likely due to the decline in opioid prescription rates starting in 2012, as evidenced by the box plots in Figure 2. The outcry from the public and regulators has led to a set of policies aimed at reducing opioid abuse. 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 this data between providers and authorities, in an attempt to reduce some opioid abuses (e.g., Buchmueller and Carey (2018)). We investigate the effects of this and other opioid-related laws in later sections.

However, as noted by prior research, many of the initial users of prescribed opioids progressed to illicit or illegal opioid use, and the opioid crisis continues to deepen. Thus, the overall opioid deaths accelerated rapidly from 2013 onward, with illicit opioid deaths in particular starting to register high growth. This latter trend is fueled by a surge in the consumption of fentanyl and other illegal opioid drugs, these latter street drugs being relatively cheap and easy to produce but extremely potent and deadly.

Figure 3 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 few shifts in these demographics over time. First, while the first wave is predominantly a White crisis, the last two opioid waves with a higher focus on illicit drugs see a significant increase in opioid deaths among minorities, too, particularly Blacks, whose opioid-related death rates surpassed White deaths in the last few years. 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. Finally, among people of various educational attainment who die from opioids, we observe a disproportionately higher percent of deaths among people with lower levels of education (high school or less) people's deaths 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.

Finally, Figures 4 and 5 provide the geographical distribution of opioid-related death rates using the confidential CDC mortality data and prescription rates using CDC/IQVIA Xponent data across counties in 2019, the last year of our sample. The darker red indicates areas with higher deaths or prescription rates. We observe stark regional variation in both measures of crisis intensity, and it is clear that the two measures are highly correlated, as evidenced by similar shades of red appearing in the same areas, despite changes in drug sources over the years.

6.2 Opioid Crisis and Marketing/Medical Practices: The Instruments

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.[21]

Formally, in order for our instruments of local opioid marketing/medical practices to be valid, they must be correlated with opioid abuse intensity. Figures 6-7 depict the geographical distribution of our two instruments across U.S. counties. Figure 6 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 7 presents *Purdue MKT (OxyContin Growth '97-'02)*, the percentage change in the quantity of OxyContin distributed by Purdue Pharma in the county between 1997 and 2002, upon the drug's introduction. Furthermore, Figure 8 presents binned scatter plots of our two opioid intensity measures, *Opioid Death Rate* and *Opioid Prescription Rate*, against the two instruments, respectively, after controlling for year and state fixed effects.

Overall, both opioid measures show a positive correlation with the two instruments, as evidenced by both the geographical distribution as well as the scatter plots. Strikingly but not sur-

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

prisingly, both opioid deaths and prescription rates are nearly perfectly positively correlated with *MKT Doctors/1000Pop*, as seen in Figure 8. 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 early distribution. The relationships between deaths and prescription rates with *High Purdue MKT (OxyContin Growth '97-'02)*, though relatively weak by comparison, also exhibit a clear positive correlation. It is reasonable to believe that the more aggressive marketing campaigns the pharmaceutical industry ran targeting doctors in an area, the higher the likelihood that marketed doctors would prescribe opioids to their patients and more of their patients would become addicted and suffer overdoses.

Furthermore, Tables 2 and 3 (Panel A) for credit performance and Tables 7 and 8 (Panel A) for credit supply below more formally discuss the first-stage estimation results for the consumer credit performance using FRBNY CCP and credit supply using Mintel/TransUnion Match File analyses. Those analyses document a significant positive association between our measures of opioid abuse intensity and the two instruments, 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 instruments are relevant and valid.

Having established that our instruments satisfy the relevancy requirement, we now turn to discussing whether they also satisfy the exclusion requirement. 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. There are reasons to believe that the exclusion condition holds. 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 only explain 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.[22] We confirm in Panel C of Table 1 that there exists little correlation between our instruments, particularly *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.

6.3 Main Results

6.3.1 Consumer Credit Performance

Table 1 Panel A provides summary statistics for the main variables of interest from the FRBNY CCP dataset. About 73% of the consumers in the sample are of working age (between 25 and 64 years old); 38% have a credit score of 620 or below. The average consumer has about 7.74 in *Ln(Credit Card Balance)* or $2,300 for those with credit cards, 9.45 in *Ln(Auto Balance)* or $12,708 for those holding car loans, and 12.00 in *Ln(First Mortgage Balance)* or $162,704 for those holding first mortgages. Note that the variances are fairly large on these balances. Since our marketing data (*MKTDoctors/1000Pop*) are only available from 2013 onward, we lose a fair number of observations in the sample when employing this instrumental variable.

We identify a credit performance issue as the first time a borrower becomes 90 days past due on a loan, *90+ Past Days Due Credit Card (%)*. Table 2 presents the IV 2SLS estimates (first and second stages) for the credit cards, conditional on consumers owing credit card debt, when using *MKTDoctors/1000Pop* (the number of physicians receiving marketing for opioids per 1,000 county population) as an instrument, while Table 3 presents the estimates when using *High Purdue MKT '97-'02* (the growth rate in pre-sample distribution of OxyContin by Purdue Pharma over 1997-2002) as an instrument for opioid abuse intensity. For brevity, we only include the coefficients of interest, but show results with full set of controls for credit cards in Appendix Table A2.[23] Table 4

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

[23]Additional results are available upon request.

shows the IV 2SLS estimates (second stage) for auto loans and first mortgages, conditional on consumers owing these debts, respectively. The latter samples are smaller than the credit card sample, as we only study the delinquency events of those who hold positive amount of the respective debt.

We consider several specifications based on different opioid crisis intensity measures for each loan type, all lagged by one year. The consumers' exposure to the opioid epidemic is measured by their county of residence and respective opioid death (prescription) rates indicators in continuous form and as a classifier of the county into the top 50th (25th) percentile of the distribution of total opioid death (prescription) rate in a particular year, a total of six different opioid intensity proxies.

This first-stage IV results in Panel A of Tables 2 and 3 indicate that both instruments strongly predict the county-level opioid deaths and prescribing rates. Then looking at the second-stage IV results in Tables 2 and 3, we find that being in a heavily opioid-exposed county significantly increases a consumer's credit card default likelihood for the subprime consumers only, controlling for several consumer characteristics including an indicator for *Subprime* (Equifax Risk Score $<$ 620), age ranges, and several debt balances, as well as variation in economic and demographic conditions in the consumer's county and other local market differences over time. Table 4 shows similar evidence for auto loans and first mortgages, again in the subprime consumers category. OLS estimations in Appendix Table A3 Panel A lead to similar conclusions. In the unreported results using an alternative definition for consumer default as 60 days past due on a loan as the key dependent variable findings are similar. We also see consistent outcomes when rerunning models for a sample that starts earlier in 2007, results are reported in Appendix Table A3 Panel B.

In terms of economic significance, the 90-day delinquency rates for credit card, auto loans, as well as first mortgages average 2.8%, 3.9%, and 2.2%, respectively. Using estimates in Tables 2, 3, and 4 that control for the endogeneity of the opioid crisis intensity when employing *MKTDoctors/1000Pop* and *High Purdue MKT '97-'02* instruments, our results indicate that for the subprime consumers living in high-opioid deaths counties, a one-standard deviation increase in the county-level death rate leads to a 26% and 40% increase in credit card default rates, a 10% and 16% increase in auto loan default rates, and a 6% and 17% increase in default rates in first mortgage loans, all for subprime consumers. Results are similar when using the opioid prescription rate or various percentiles for deaths and prescriptions as the opioid exposure.[24]

To summarize, our analyses of consumer-level credit defaults suggest significant credit risk associated with subprime 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 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. This labor channel alone would lead to enhanced credit risk, according to the model presented earlier.

6.3.2 Bank Consumer Loan Portfolio Performance

Given that consumers in areas hard-hit by opioids are more likely to default on their financial obligations if they are more vulnerable (subprime), we next test whether banks more exposed to the opioid crisis via their local branch network or operations suffer more from nonperforming loans and charge-offs across their consumer loan portfolios. We also check whether exposed banks that operate in only one county are likely to have a harder time diversifying their risk exposure from the opioid crisis, and hence may suffer even more than their exposed multi-county counterparts. According to Table 1 Panel E, on average, a bank in our Call Reports data has a Tier 1 capital ratio of 17.2%, liquidity of 28.5%, quarterly return on assets of roughly 1%, bank size (natural logarithm of total assets) of 12.2, and age of 76 years.

We begin with credit card debt. Table 5 and Appendix Table A4 report the OLS and IV regression estimates for the effects of the opioid crisis on bank credit card non-performing loans (NPL) and net charge-off ratios for all banks and just single-county ones over 2010-2019, respectively. Panel A reports OLS estimates, while Panel B reports second-stage IV estimates when using a bank's exposure to *High Purdue MKT '97-'02* as an instrument for exposure to high opioid crisis intensity. In both cases, the exposure of a bank to opioids is measured as a weighted average using a bank's proportion of branches across the counties of operation as the weights. The key dependent variables are either bank NPL for credit cards (%) or bank net charge-offs for credit cards (%). The main independent variables of interest are the six opioid intensity measures discussed previously, corresponding to a bank's exposure to either continuous opioid deaths and prescription rates or

[24] Our results on auto loans are comparable with Jansen (2021).

dichotomous indicators of exposure to high opioid abuse areas marked at the top 50th and 25th percentiles in different specifications. We control for bank financial health including bank capital and liquidity ratios, profitability, bank size, and age. We also include a rich set of indicators of economic and demographic local market conditions beyond the opioid epidemic (all county-level controls from prior analyses, this time aggregated at the bank level based on a bank's branches' presence in different markets). Bank fixed effects in our models control for other unobserved features at the bank level, and year fixed effects account for unobserved heterogeneity across time, such as changes in economic conditions that are not captured by the control variables and changes in regulation that affect all banks at the same time.

We find that banks with a higher exposure to counties more affected by opioid abuse incur significantly higher non-performing credit card loans as well as higher net charge-offs on credit card loans. We reach similar conclusions for single-county banks. Banks confined to more severely affected counties report higher non-performing loans and net charge-offs in credit card products. Moreover, coefficients for those highly concentrated banks are much larger, sometimes several times larger, compared to the results for all banks. These results are consistent with single-county banks not able to stay away from the hard-hit locations where they operate or diversify their portfolios geographically. In unreported results, findings are also consistent if we rerun models using a sample starting earlier in 2007.

The economic impact of the observed increase in non-performing loans and charge-offs is sizable. For each additional 1 death per 1 million population, we see an increase in non-performing credit card loans (net charge-off) ratio of 0.007% (0.006%) for single-county banks and 0.0014% (0.0011%) for all banks. While the nominal numbers look small, the effects are economically significant relative to the bank average non-performing loans (net charge-off) ratio of 0.004% (0.003%).

Importantly, our findings for total consumer loans presented in Table 6 and Appendix A Table A5 are consistent with those for credit card loans. These additional results further corroborate our first two analyses and demonstrate that banks' higher exposure to the opioid crisis induces increased credit risk across their entire consumer loan portfolio.

6.3.3 Consumer Credit Supply

If banks are aware of the risks associated with exposure to opioid abuse and recognize the resulting heightened credit risk, they will react. We next analyze whether banks changed their credit card supply in counties with higher opioid crisis intensity, by looking at 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 B presents summary statistics for the key variables used in this part of the analyses. Without going into great details, we note that the average consumer in our Mintel/TransUnion Match File dataset has a VantageScore 3.0 of 717, *Ln(Consumer Income)* of \$10.9 or \$59,874, suggesting that a typical consumer in the study has a relatively good financial profile. In other details, we find that 19% of the consumers have had at least one 90+ days past due delinquency on any credit product, 6% have filed for bankruptcy, and 2% have high credit card utilization (80% or higher) in the past. Demographically, the average consumer is 51 years old, 80% of consumers are homeowners, 42% are married, and 51% have no children.

Tables 7 and 8 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* and *High Purdue MKT '97-'02* instruments, respectively. As above, for brevity, we only include the coefficients of interest but show results with a full set of controls for credit cards in Appendix Table A6. The key dependent variables are either *Rate Spread*, the APR credit card spread, or *Ln(Limit)*, the natural log of the offered credit card limit. The main independent variables are the six opioid intensity measures all lagged 1 year, corresponding to continuous opioid deaths and prescription rates or indicators for high opioid abuse marked at the top 50th and 25th percentiles in different specifications. 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 county characteristics, State and Year-Month fixed effects, to account for other unobserved heterogeneity across local markets and time, and Lender × Year-Month fixed effects to absorb variation in lender conditions over time.

In all cases, the IV first-stage estimates indicate that our instruments are significantly positively associated with higher opioid crisis intensity. 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.[25] These consumers are offered higher credit card APR spreads and lower credit card limits. These results are further corroborated by a reduction in credit supply at the extensive margin in Table 10, where the dependent variable is a binary for the likelihood of a consumer getting a credit card offer and includes a larger Mintel/TransUnion Match File sample that covers consumers with and without credit card offers. We find that consumers in counties with higher opioid crisis intensity are less likely to receive credit card offers, while also controlling for many consumer credit quality metrics as well as other supply and demand factors. Taken together, these results indicate that banks reduce consumer credit supply at both intensive and extensive margins in the counties that are more hardly hit by the opioid crisis.

Our credit supply results are also economically significant. The average *Rate Spread* is 16.1 percentage points and *Ln(Limit)* is 6.6. Using estimates in Table 7 that control for endogeneity of the opioid crisis intensity when employing *MKTDoctors/1000Pop* as an instrument, our results indicate that based on a one-standard deviation increase in county-level death rate for the continuous measure or moving from a low- to high-opioid abuse rate county for the binary opioid measures is associated with a 0.6 to 1.1 percentage points increase in credit card interest rates and a 7% to 15% decrease in credit card limits for consumers living in more opioid-affected counties. Similarly, as shown in Table 8, using *High Purdue MKT '97-'02* as an instrument, we find economically meaningful tightening of credit card offer terms for consumers. Table 10 further shows a significantly lower probability of a credit card offer to a consumer while controlling for endogeneity of the opioid crisis intensity using different instrumental variables. Economic magnitudes range

[25] Appendix Table A7 supports similar conclusions using OLS estimations. Findings are also consistent when rerunning models for a sample that starts earlier in 2007, which we report in Appendix Table A8.

from 0.4% to 7% lower likelihood of getting an offer for consumers in hardly hit areas when using *MKTDoctors/1000Pop* as an instrument, and similar conclusions can be reached with *High Purdue MKT '97-'02* as an instrument. Thus, the opioid epidemic appears to induce significant reductions in bank credit supply to consumers.

6.4 Additional Identification Tests

Additional Opioid 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 A9 reiterates our main results for credit supply terms for consumers when looking separately at rates of prescription and illicit opioid deaths. Panel A reports IV second-stage results when using *MKTDoctors/1000Pop* as instrument, while Panel B reports IV results when using *High Purdue MKT '97-'02* as the instrument for opioid abuse intensity. We do find significant increases in credit card spreads and lower credit card limits from both types of death rates, however, magnitudes and significance tend to be larger for the illicit opioid deaths, as expected. In untabulated tests, we further conduct tests when using individual opioid death rates by races, genders, age groups, and education groups. All these different opioid proxies yield a consistent message: Higher opioid intensity from any of these demographic groups significantly results in a contraction of credit supply to consumers, consistent with our main findings.

Additional Identification and Other Checks We next conduct a number of additional identification tests for the credit supply analysis to ensure that results do not suffer from self-selection bias, potentially omitted variable bias, or measurement error concerns. We discuss each of those below.

Self-Selection Concerns 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 a non-parametric propensity score matching (PSM) analysis in Table 9 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. Second, we 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. Then, we also 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.

In another approach as reported in Table 9 Panel B, 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. Neighboring counties are assumed to have very similar economic and other conditions, making the two groups more comparable. We then rerun our main regression analysis using this constrained sample. Despite the significant loss in the number of observations, results continue to show harsher credit card terms for consumers in highly affected opioid counties.

Potential Outlier Counties We also perform several tests to ensure that no outlier counties drive our results, and report results in Appendix Table A10. Thus, we rerun our main credit supply results when excluding Florida in Panel A, an epicenter for the opioid crisis with many "pill mill" pharmacies and particularly lax opioid regulation. We also exclude counties with "zero deaths" reported in Panel B to ensure that they do not drive our results. Finally, we exclude top and bottom 5% of counties in terms of population density, income, and unemployment rate in Panels E-G, to ensure that no important county characteristics could be responsible for the documented results. Our main findings are confirmed in all cases.

Omitted Variable Concerns Omitting important credit demand and supply factors that might be correlated with the opioid crisis intensity could significantly bias the coefficients. We address this issue in the main analysis by saturating the model with many demand and supply controls, including customer and local market characteristics, as well as fixed effects for banks over time, local markets, and year-month. We perform several additional analyses to further address the above concern. We rerun our main results when we control for even more county characteristics including labor participation rate, average credit score, air pollution index, house price index, percent of school dropouts, percent of religious population, politics (ratio of Democratic to Republican votes in each electoral year), poverty rate, percent of people with poor health, and crime rate.[26] We report results in Table 9 Panel E and Table A10 Panel D. We also include State x Year-Month fixed effects to control for changes in local market conditions over time. Finally, to address concerns that credit card terms may be correlated within an offer campaign over time, we adjust standard errors for clustering at the campaign level and by campaign and year-month level to allow for correlations among different campaigns in the same time period. Results hold in all these checks.

Potential Measurement Error The opioid crisis intensity variables are approximations based on death information from the CDC and we use underlying death cause as our main source. If such death-rate metrics are measured with noise as a lot more individuals die from opioids, but the underlying cause of death does not get recorded as opioid related, measurement errors can result in biased estimates. We confront this potential problem by replacing our main opioid death rate measure based on underlying causes with an alternative measure that counts any opioid deaths among the multiple causes of death of the individual, and report results in Table A10 Panel C. Our main findings are robust to the use of this alternative opioid intensity proxy.

6.5 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. The richness of our credit supply data allows us to test this conjecture as reported in Table 11 Panels A-D and Appendix Table A11 Panels A-B, using interactions between the opioid crisis intensity and consumer high-risk indicators, while using *MKTDoctors/1000Pop* as an instrument for opioid abuse intensity. Results from the IV second stage are reported in these tables. The consumer risk metrics utilized are indicators for *Subprime* (VantageScore 3.0 be-

[26] These additional variables are sourced from the U.S. Census American Community Surveys, the Social Explorer (U.S. Health Data; U.S. Religion Data (InfoGroup); U.S. Crime Data (FBI)), the Federal Housing Finance Agency (FHFA), and the MIT Election Lab.

low 580), past deep delinquency, past derogatory filings, high past credit utilization ratio ($\geq$80%), bankruptcy filings, and low income ($<$30K). Across all these risk measures and six different opioid intensity measures, we consistently observe that banks apply additionally harsher credit terms for riskier consumers in highly opioid-affected counties.

In Tables 12 and 13 and Appendix Table A11, we analyze additional IV results (using *MKTDoctors/1000Pop* as an instrument for opioid abuse intensity) with heterogeneous effects across several consumer demographic characteristics that were shown to matter for the opioid crisis evolution over time. Specifically, Table 12 reports cross-sectional tests when interacting the opioid intensity measures with an indicator for minority consumers in Panel A, and with individual minority group indicators in Panel B. Table 13 Panels A-B and Appendix Table A11 Panels C-D show cross-sectional tests when interacting opioid intensity measures with indicators for young consumers ($<$ 25 years old), working age consumers (25-64 years old), female, and low education (less than college). We note a much smaller sample when testing interactions with female consumers as we only include observations for which gender can be cleanly identified in the dataset. Finally, in untabulated results, we run similar cross-sectional tests for consumers who are married or have no kids. Our results suggest that minorities, particularly Blacks, as well as young consumers, face additionally harsher terms when living in highly opioid-affected counties. The latter results can suggest that banks may perceive these consumers as posing higher possibility of delinquency and default and/or other potential statistical discrimination reasons. We do not observe any additional effects on consumers having low education or no kids and see only very weak harsher effects on females in few instances. Additional credit effects on married consumers are mixed.

6.6 Effectiveness of Recent Opioid Policies

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 estimating the implications of those regulations either yield mixed results or only consider 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 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 four are time-varying with a staggered implementation and two are time-invariant over our sample period. We focus on the impact on credit supply as this is the margin that has the most implications on local economic recovery.

We take advantage of the staggered implementation of the first four state-level opioid laws designed to combat opioid abuse by running a difference-in-difference (DID) regression specification to evaluate the effectiveness of the laws and their influence on consumer finance. These time-varying laws are as follows. First, we consider state opioid laws that explicitly set limits on prescriptions of opioids. Thus, certain states would limit prescriptions to a 4-, 5-, or 7-day supply for first time users or for acute or postoperatory 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 this 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, we consider PDMP Laws that 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.[27] We focus on the mandatory PDMPs in our analysis given prior research finds these

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

to be more likely to affect behavior, but also conduct robustness using all the PDMPs and find consistent results.

Third, we include Naloxone access laws that increase 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)). Fourth, we consider Good Samaritan Law, which 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.

Fifth, we consider the Triplicate Prescription Law, which requires 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 prescriptions via special prescription documentation in triplicate requirement substantially reduces opioid use and related deaths in those states once epidemic unfolds. The requirement was in effect in the states of California, Idaho, Illinois, New York, and Texas. Finally, we also consider Medical Marijuana Permitting Law whose 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)).[28] The last two laws are time-invariant over our sample period.

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 Appendix Table A12 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 year fixed effects for the state time-invariant ones, given that the laws are at the state level.

Conditional on a strong set of controls for local markets and time, we uncover very different impacts among those laws. All types of laws except the Naloxone Law help reduce opioid

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

prescription rates with strongest effects for the states with triplicate prescription, the PDMPs, and Medical Marijuana permitting laws. However, effects on opioid deaths are more nuanced. Most laws tend to increase rather than decrease overall opioid deaths, an exception being the triplicate prescription law, which has a strong death reducing effect. However, when we split opioid death rates into prescription and illicit deaths, we can see that in addition to the triplicate law, also the prescription state limiting law, the mandatory PDMPs, and the Medical Marijuana permitting law all help reduce opioid deaths from prescription opioids but the effects are reversed for illicit opioids. 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. 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.[29]

Finally, Table 14 conducts a horse race among the effects of different state laws on consumer credit supply. We show the effects of time-varying state laws in Panel A, and sample splits for the time-invariant laws in Panels B and C. 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 second stage estimates in all cases.

Table 14 Panel A shows that the Opioid Prescription Limiting Law and the mandatory PDMPs yield positive effects on consumer credit supply, which reverse some of the negative consequences of the opioid crisis, but the Naloxone and Good Samaritan Laws have either no effects or some negative effects on credit supply for consumers. Finally, Panels B and C strongly show that there are no negative credit supply effects on consumers in states that implemented triplicate prescription laws and those that did not implement a Medical Marijuana permitting law. To conclude, some laws (the opioid prescription limiting law, the mandatory PDMPs, and the triplicate prescription law) tend to have positive reversal effects on consumer market credit supply, while others (Naloxone, Good Samaritan, Medical Marijuana Permitting Laws) appear to help less or even induce some

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

detrimental effects on consumer credit, and potentially intensify the crisis. The different effects are likely due to the different nature and intent of the laws, and are consistent with prior research. But importantly, laws that do have beneficial effects on reducing opioid prescriptions and deaths also tend to exhibit mitigating effects in consumer credit supply.

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. We discover unfavorable credit consequences of this crisis for both consumers and banks: 1) Lower-credit-score consumers in the opioid-affected areas are more likely to default on their credit card, auto, and mortgage loans; 2) Banks exposed to higher opioid crisis severity via their local market operations incur higher consumer portfolio risk (higher nonperforming loans and net charge-offs); 3) Consequently, banks become 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 higher interest rates and lower credit limits. The credit supply constriction seems to harm harder the riskier consumers as well as minorities and younger people.

From a policy standpoint, the cautious behavior of banks appears to be justified. The reduced consumer credit supply, nevertheless, could create a negative feedback loop depriving the opioid-affected regions of the much-needed liquidity for recovery. Existing regulations have had mixed effects in reducing opioid abuse and hence in stimulating credit supply in regions hit hard by the opioid crisis.

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Figure 1 : **Opioid Crisis Over Time (Waves)**

This box plot depicts the timeline of the opioid crisis and plots total opioid-related death rates per 10K population over time. Data sources: CDC/NCHS, National Center for Health Statistics, Mortality.

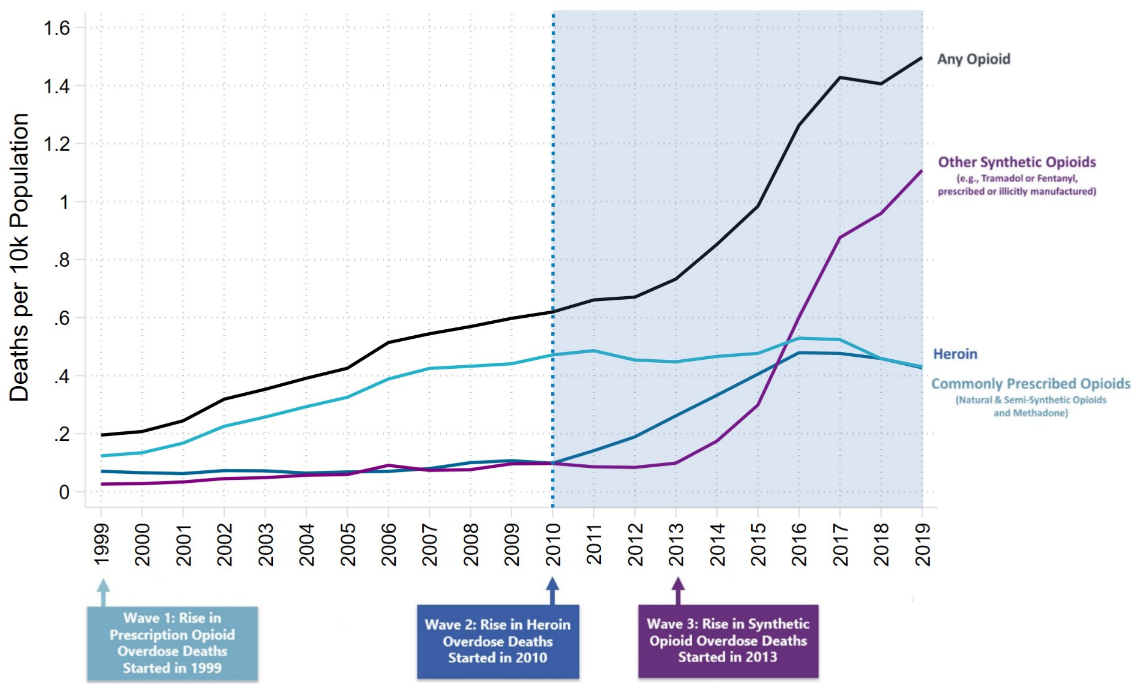


Figure 2 : **Opioid-Related Death Rates and Prescription Rates Over Time**

This box plot depicts the time trend of total opioid-related death rates and Opioid Prescription Rates. The death rates are total opioid-related death rates per 10k population. The prescription rates are total opioid prescriptions per 100 population. The boxes represent the middle 50 percent of the distribution, with the middle line indicating the median, the top box line indicating the 75th percentile, and the bottom box line indicating the 25th percentile. Data sources: CDC/NCHS, National Center for Health Statistics, Mortality.

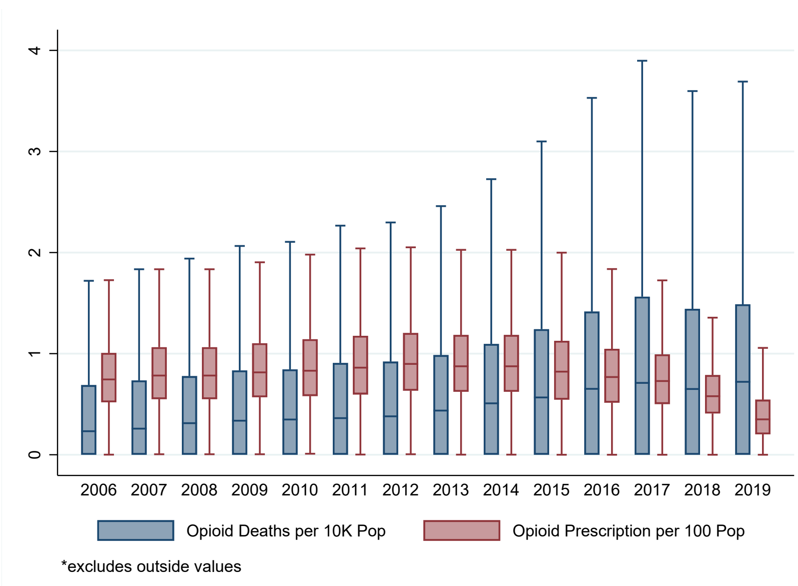
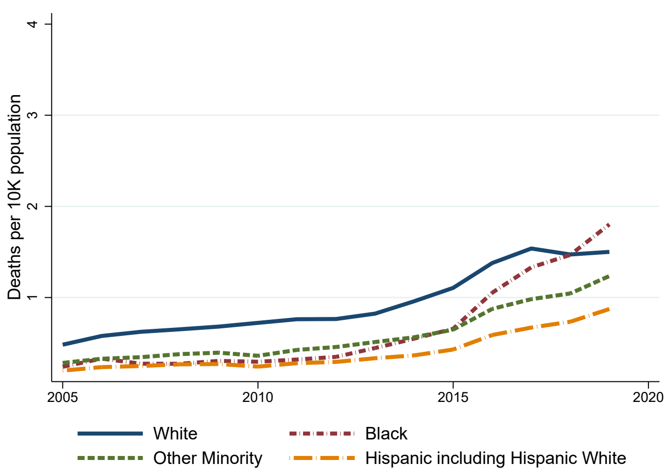


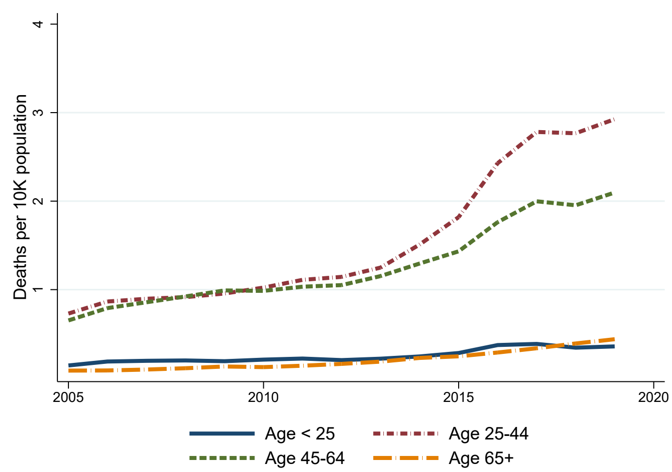
Figure 3 : **Opioid Death Rates by Consumer Demographics**

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.

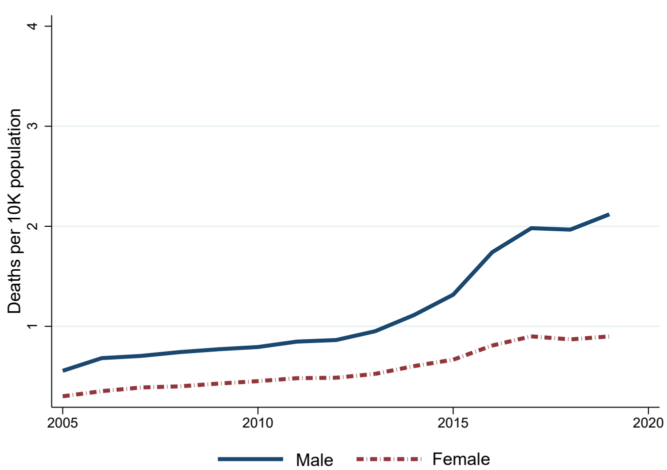
Panel A: **Opioid Death Rates by Consumer Race**



Panel B: **Opioid Death Rates by Consumer Age**



Panel C: **Opioid Death Rates by Consumer Gender**



Panel D: **Opioid Death Rates by Consumer Education**

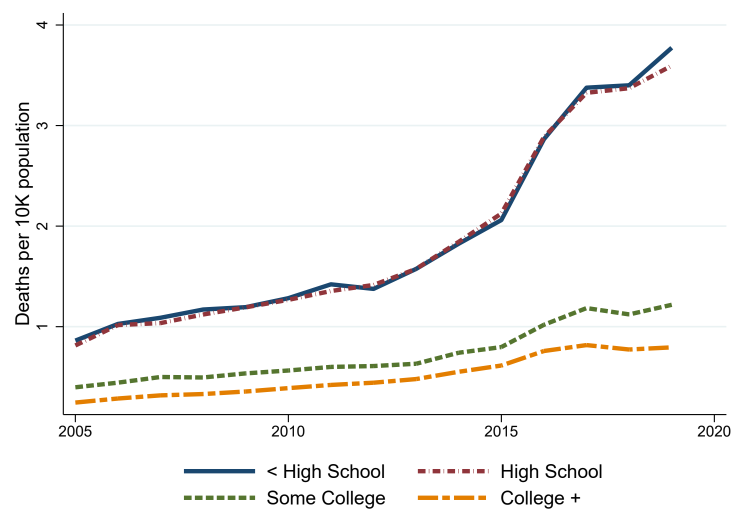


Figure 4 : **Opioid-Related Death Rates Across U.S. Counties in 2019**

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.

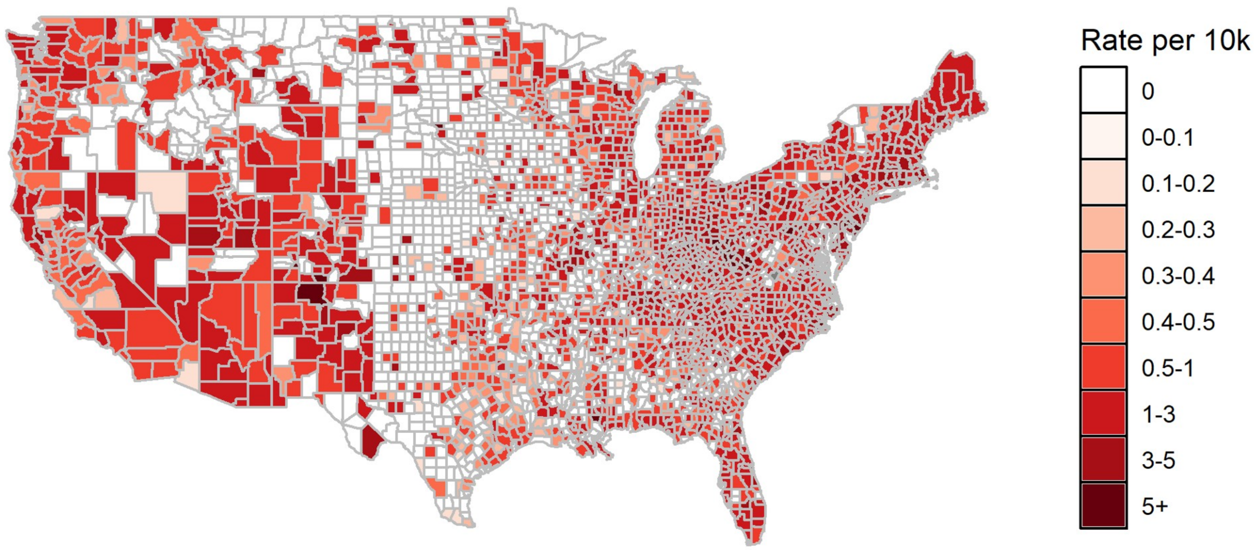


Figure 5 : **Opioid Prescription Rates Across U.S. Counties in 2019**

This figure presents the geographical distribution of opioid prescription rates (per capita) across U.S. counties for year 2019. Darker red colors represent higher prescription rates. Data sources: CDC/IQVIA Xponent.

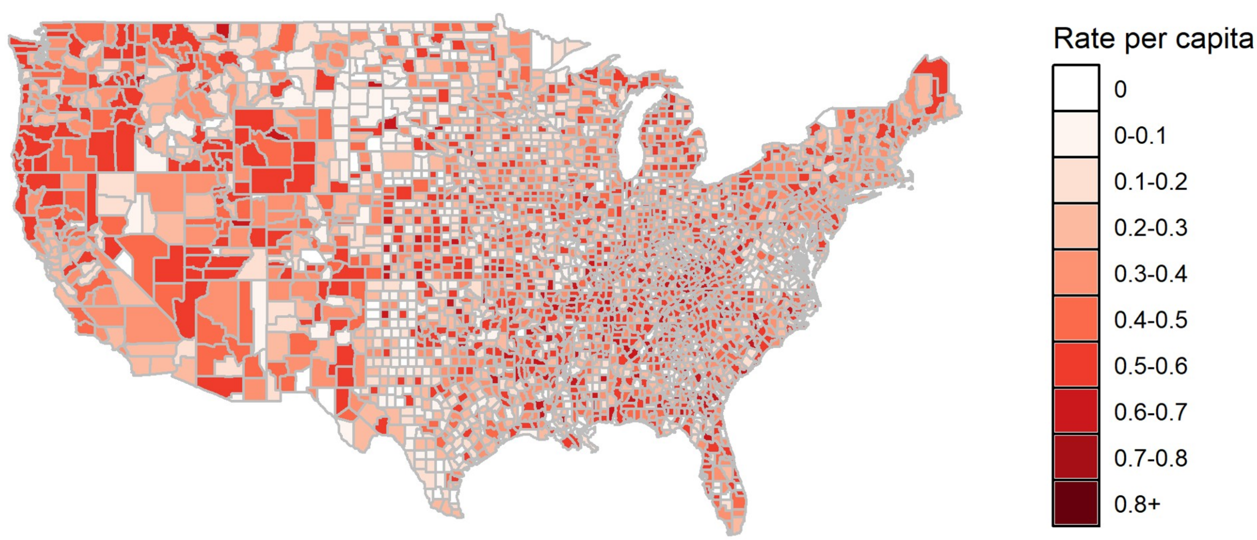


Figure 6 : **Instrument** *MKT Doctors/1000Pop* **across U.S. Counties over 2013-2019**

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).

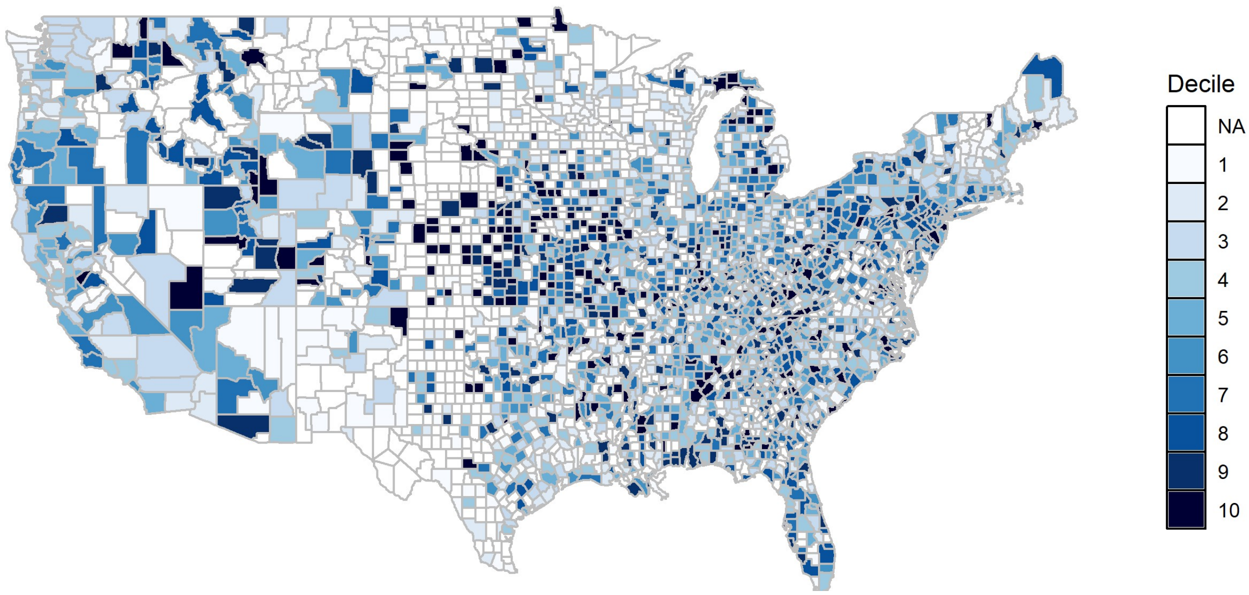


Figure 7 : **Instrument** *Purdue MKT (OxyContin Growth '97-'02)* **across U.S. Counties**

This figure presents the geographical distribution of Purdue Pharma OxyContin opioid distribution across U.S. counties over 1997-2002, a proxy of aggressive opioid marketing prior to our sample period. 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: U.S. Drug Enforcement Administration (DEA) and Cornaggia, Hund, Nguyen and Ye (2021).

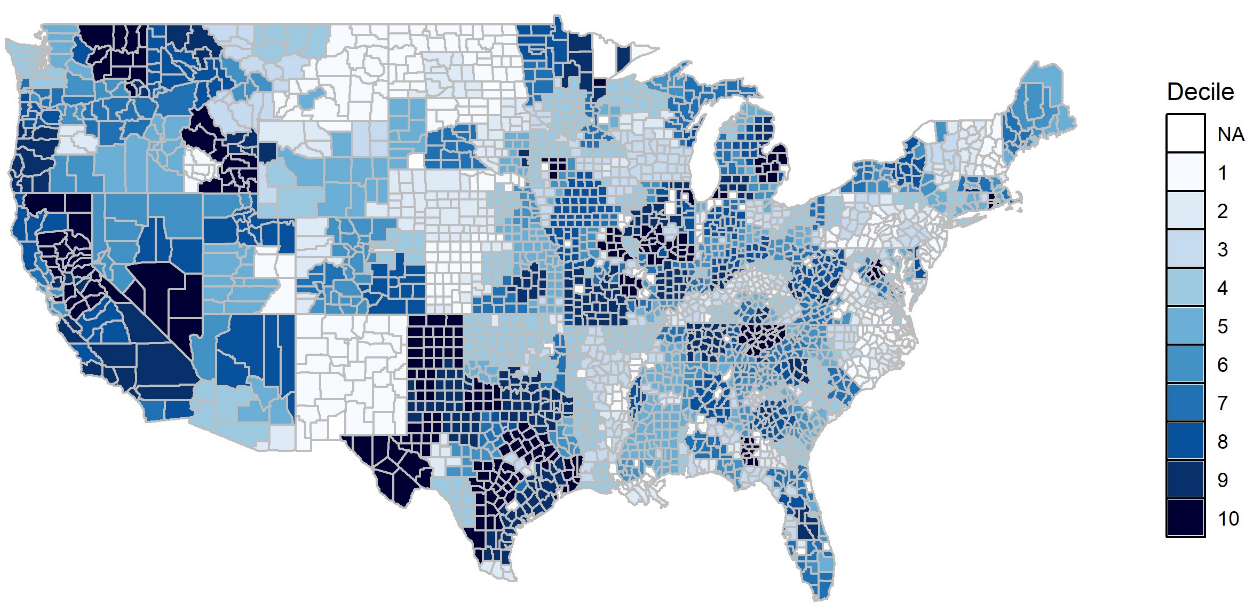
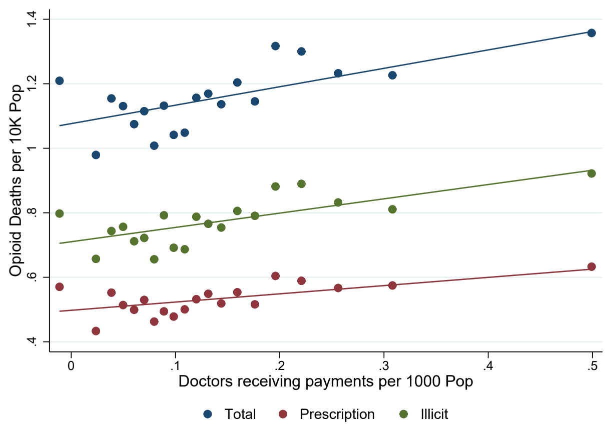


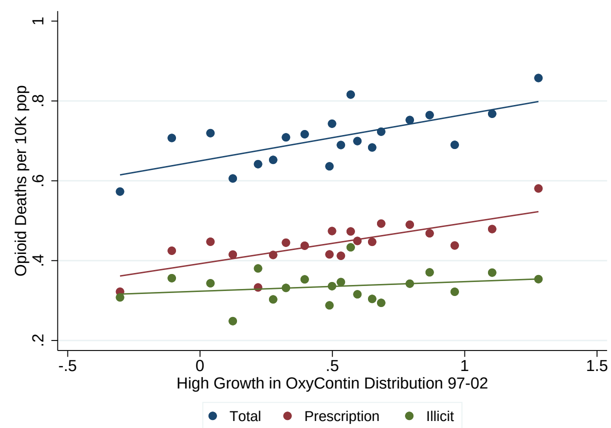
Figure 8 : **Validating the Instruments: Relevancy**

This figure provides binned scatter plot of opioid-related deaths per 10K population as well as opioid prescription rate per 100 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; and versus the high distribution growth of OxyContin pills by Purdue Pharma (*High Purdue MKT (OxyContin Growth '97-'02)*) between 1997 and 2002 after taking out the state and year fixed effects. 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).

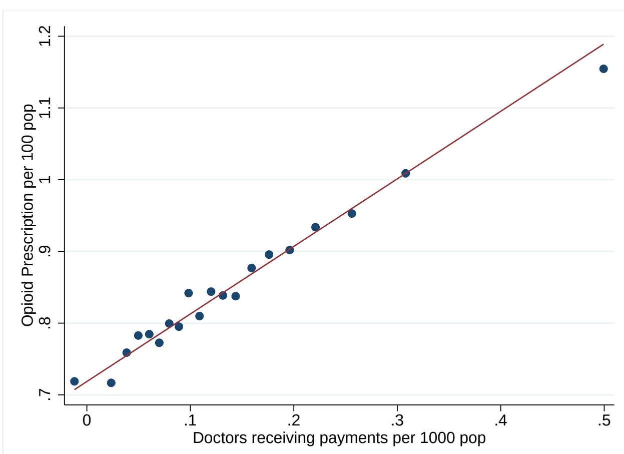
Panel A: **Death Rate vs.** *MKT Doctors/1000Pop*



Panel B: **Death Rate vs.** *High Purdue MKT (OxyContin Growth '97-'02)*



Panel C: **Prescription Rate vs.** *MKT Doctors/1000Pop*



Panel D: **Prescription Rate vs.** *High Purdue MKT (OxyContin Growth '97-'02)*

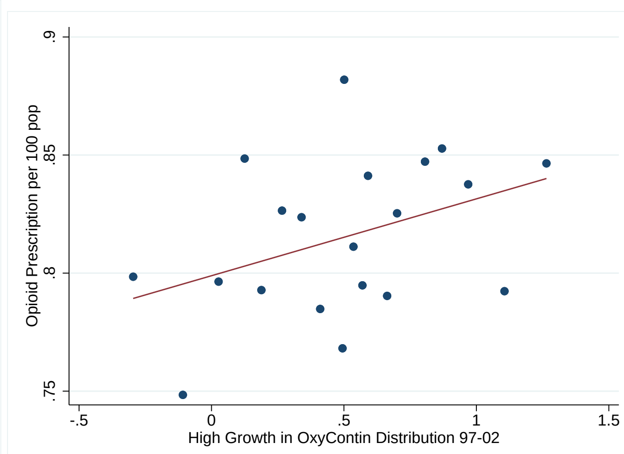


Table 1: **Summary Statistics**

This table reports 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 in Panel A consists of a 2.5% random sample comprising consumers between the age of 18 and 85 from the anonymized FRBNY Consumer Credit Panel/Equifax Data (FRBNY CCP). The credit card balance, auto loan balance and first mortgage balances, and their respective default status are reported only for consumers with positive credit card debt, auto loan, or first mortgages in the dataset. Panel B shows statistics based on bank public Call Reports and FDIC Summary of Deposits. The sample in Panel C 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. VantageScore and score ranges are based on the VantageScore 3.0. All demographic attributes are from the Mintel. Panel D shows correlations of our instrumental variables (*MKT Doctors/1000Pop* and *Purdue MKT (OxyContinGrowth '97-'02)*) with county economic and other characteristics. All sample variables are over 2010-2019, except for the instrument *MKT Doctors/1000Pop*, which is over 2013-2019 due to data availability.

Panel A: FRBNY CCP (2010-2019, Annual)

Variable	mean	p50	sd	p25	p75	N
Key Dependent Variables						
90+ Days Past Due: Credit Card	0.028	0.000	0.170	0.000	0.000	1,480,011
90+ Days Past Due: Auto Loan	0.039	0.000	0.190	0.000	0.000	827,508
90+ Days Past Due: First Mortgage	0.022	0.000	0.150	0.000	0.000	764,901
60+ Days Past Due: Credit Card	0.035	0.000	0.180	0.000	0.000	1,480,011
60+ Days Past Due: Auto Loan	0.045	0.000	0.210	0.000	0.000	827,508
60+ Days Past Due: First Mortgage	0.028	0.000	0.170	0.000	0.000	764,901
Key Independent Variables						
Opioid Death Rate	0.940	0.710	0.870	0.400	1.220	2,537,841
Prescription Opioid Death Rate	0.480	0.380	0.420	0.200	0.630	2,537,841
Illicit Opioid Death Rate	0.570	0.320	0.760	0.140	0.690	2,537,841
Opioid Prescription Rate	0.710	0.660	0.340	0.470	0.880	2,530,655
Instrumental Variables						
MKT Doctors/1000Pop	0.130	0.110	0.092	0.069	0.180	1,465,295
High Purdue MKT (OxyContin Growth '97-'02)	0.550	1.000	0.500	0.000	1.000	2,520,524
Purdue MKT (OxyContin Growth '97-'02)	6.150	5.300	3.590	3.860	7.680	2,520,524
Consumer & Loan Characteristics						
Age_25to44	0.360	0.000	0.480	0.000	1.000	2,538,458
Age_45to64	0.370	0.000	0.480	0.000	1.000	2,538,458
Age_65plus	0.190	0.000	0.390	0.000	0.000	2,538,458
CreditScore_580_660	0.180	0.000	0.380	0.000	0.000	2,538,458
CreditScore_660_720	0.160	0.000	0.370	0.000	0.000	2,538,458
CreditScore_720_800	0.270	0.000	0.440	0.000	1.000	2,538,458
CreditScore_800plus	0.190	0.000	0.390	0.000	0.000	2,538,458
Ln(Credit Card Balance)	7.740	7.780	1.980	6.560	8.880	1,480,011
Ln(Auto Balance)	9.450	9.530	1.090	8.940	10.000	827,508
Ln(First Mortgage Balance)	12.00	11.90	1.360	11.30	12.40	764,901
County Characteristics						
Ln(County Income)	10.300	10.200	0.240	10.100	10.400	2,538,313
County Unemployment Rate	6.310	5.700	2.760	4.170	8.030	2,538,458
County Bank HHI	0.180	0.140	0.110	0.110	0.200	2,538,456
County Population Density	2163.3	588.4	6810.1	189.6	1688.8	2,538,458
County % Male	0.490	0.490	0.011	0.480	0.500	2,538,458
County Race HHI	0.690	0.670	0.170	0.550	0.800	2,538,458
County % Age_25_44	0.270	0.260	0.034	0.240	0.290	2,538,458
County % Age_45_64	0.260	0.260	0.025	0.250	0.280	2,538,458
County % Age_65plus	0.140	0.140	0.038	0.120	0.160	2,538,458
County % High Education ($\geq$ College)	0.110	0.110	0.053	0.077	0.140	2,538,458
County Inequality: Gini Coefficient	0.460	0.460	0.036	0.430	0.480	2,538,452

Table A1: **Summary Statistics (continued)**

Panel B: Call Reports (2010-2019, Quarterly)

Variable	mean	p50	sd	p25	p75	N
Key Dependent Variables						
Opioid Death Rate	0.086	0.065	0.082	0.034	0.114	272,448
Top50th_Opioid Death Rate	0.005	0.000	0.005	0.000	0.010	293,524
Top25th_Opioid Death Rate	0.002	0.000	0.004	0.000	0.000	293,524
Opioid Prescription Rate	0.761	0.719	0.368	0.502	0.948	287,760
Top50th_Opioid Prescription Rate	0.005	0.000	0.005	0.000	0.010	293,524
Top25th_Opioid Prescription Rate	0.002	0.000	0.004	0.000	0.000	293,524
Key Independent Variables						
NPL Total Consumer	0.339	0.138	0.675	0.019	0.395	221,642
NPL Credit Cards	0.004	0.000	0.078	0.000	0.000	278,068
NPL Unsecured Consumer	0.016	0.000	0.146	0.000	0.004	279,801
NPL Secured Consumer	0.320	0.126	0.654	0.012	0.371	221,642
Net Charge-Offs Total Consumer	0.017	0.001	0.177	0.000	0.014	222,238
Net Charge-Offs Credit Cards	0.003	0.000	0.142	0.000	0.000	279,438
Net Charge-Offs Unsecured Consumer	0.008	0.000	0.147	0.000	0.003	279,438
Net Charge-Offs Secured Consumer	0.012	0.000	0.087	0.000	0.009	222,245
Instrumental Variables						
High Purdue MKT (OxyContin Growth '97-'02)	0.690	1.000	0.460	0.000	1.000	272,304
Bank Characteristics						
Tier1 Capital	0.172	0.148	0.096	0.122	0.191	277,904
Liquidity	0.285	0.259	0.173	0.159	0.387	279,801
Profitability	0.005	0.004	0.075	0.002	0.008	279,692
Bank Size	12.212	12.077	1.318	11.352	12.906	279,801
Bank Age	76.117	87.023	43.768	32.113	110.053	282,328
County Characteristics						
Ln(County Income)	10.641	10.626	0.263	10.476	10.783	293,032
County Unemployment Rate	0.064	0.060	0.027	0.042	0.082	293,524
County Bank HHI	0.217	0.187	0.124	0.133	0.265	293,488
County Population Density	2712.52	200.95	16273.86	61.02	1091.38	293,524
County Race HHI	1.973	1.903	1.286	0.807	3.068	293,524
County % Male	1.271	1.373	0.729	0.525	1.970	293,524
County % Age_25_44	0.642	0.698	0.383	0.271	0.976	293,524
County % Age_45_64	0.685	0.753	0.400	0.288	1.065	293,524
County % Age_65plus	0.391	0.388	0.254	0.158	0.579	293,524
County % High Education ($\geq$ College)	1.378	1.396	0.852	0.572	2.118	293,524
County Inequality: Gini Coefficient	1.137	1.260	0.661	0.483	1.744	293,524

Table 1: **Summary Statistics (continued)**

Panel C: Mintel/TransUnion Match File Sample (2010-2019, Monthly)

Variable	mean	p50	sd	p25	p75	N
Key Dependent Variables						
Rate Spread	16.086	14.000	4.859	12.800	19.900	371,223
Ln(Limit)	6.553	6.217	0.869	6.217	6.909	371,223
Limit ($)	1131.852	500.000	1409.810	500.000	1000.000	371,223
Credit Card Offer	0.587	1.000	0.492	0.000	1.000	752,275
Key Independent Variables						
Opioid Death Rate	0.956	0.728	0.887	0.393	1.235	371,223
Top50th_Opioid Death Rate	0.503	1.000	0.500	0.000	1.000	371,223
Top25th_Opioid Death Rate	0.253	0.000	0.435	0.000	1.000	371,223
Prescription Opioid Death Rate	0.484	0.396	0.424	0.200	0.649	371,223
Illicit Opioid Death Rate	0.577	0.310	0.784	0.130	0.695	371,223
Opioid Prescription Rate	4.845	3.974	4.219	2.012	6.493	369,646
Top50th_Opioid Prescription Rate	0.504	1.000	0.500	0.000	1.000	369,646
Top25th_Opioid Prescription Rate	0.252	0.000	0.434	0.000	1.000	369,646
Instrumental Variables						
MKT Doctors/1000Pop	0.140	0.120	0.093	0.072	0.188	197,739
High Purdue MKT (OxyContin Growth '97-'02)	0.501	1.000	0.500	0.000	1.000	369,587
Purdue MKT (OxyContin Growth '97-'02)	6.019	5.211	3.509	3.757	7.315	369,587
Consumer & Loan Characteristics						
Consumer Credit Score	716.890	725.000	92.298	646.000	796.000	371,223
Credit Score_580_660	0.222	0.000	0.415	0.000	0.000	371,223
Credit Score_660_720	0.188	0.000	0.391	0.000	0.000	371,223
Credit Score_720_800	0.283	0.000	0.451	0.000	1.000	371,223
Credit Score_800plus	0.233	0.000	0.423	0.000	0.000	371,223
Deep_Delinq	0.185	0.000	0.388	0.000	0.000	371,223
Recent_Delinq	0.079	0.000	0.269	0.000	0.000	371,223
Other_Derogatory	0.196	0.000	0.397	0.000	0.000	371,223
Bankruptcy_Filer	0.057	0.000	0.231	0.000	0.000	371,223
High_Util ($\geq$*80%)*	0.023	0.000	0.150	0.000	0.000	371,223
Ln(1+ No Credit Inquiries)	0.311	0.000	0.497	0.000	0.693	371,223
Has_Prior_Cards	0.954	1.000	0.210	1.000	1.000	371,223
Consumer Age	50.910	52.000	15.997	38.000	63.000	371,223
Age_25to44	0.329	0.000	0.470	0.000	1.000	371,223
Age_45to64	0.427	0.000	0.495	0.000	1.000	371,223
Age_65plus	0.205	0.000	0.404	0.000	0.000	371,223
Married	0.419	0.000	0.493	0.000	1.000	371,223
No_Kids	0.505	1.000	0.500	0.000	1.000	371,223
White	0.580	1.000	0.494	0.000	1.000	371,223
Miss_Race	0.344	0.000	0.475	0.000	1.000	371,223
Educ: Some_College	0.135	0.000	0.341	0.000	0.000	371,223
Educ: College	0.156	0.000	0.363	0.000	0.000	371,223
Educ: Post_College	0.080	0.000	0.271	0.000	0.000	371,223
Miss Educ	0.239	0.000	0.427	0.000	0.000	371,223
Homeowner	0.801	1.000	0.399	1.000	1.000	371,223
Ln(Consumer Income)	10.967	11.082	0.811	10.532	11.379	371,223
County Characteristics						
Ln(County Income)	16.593	16.774	1.682	15.418	17.816	371,223
County Unemployment Rate	6.494	5.967	2.697	4.367	8.200	371,223
County Bank HHI	0.180	0.145	0.113	0.113	0.203	371,223
County Population Density	1650.486	534.413	5065.595	165.580	1529.734	371,223
County Race HHI	0.696	0.683	0.193	0.560	0.825	371,223
County % Male	0.492	0.491	0.011	0.485	0.497	371,223
County % Age_25_44	0.263	0.262	0.032	0.242	0.285	371,223
County % Age_45_64	0.264	0.266	0.026	0.247	0.281	371,223
County % Age_65plus	0.140	0.135	0.038	0.115	0.157	371,223
County % High Education ($\geq$ *College)*	0.584	0.589	0.096	0.523	0.649	371,223
County Inequality: Gini Coefficient	0.451	0.451	0.035	0.427	0.472	371,223

Table 1: **Summary Statistics (continued)**

Panel D: Correlations of Instruments with County-Level Economic & Other Conditions

Correlation	*MKT Doctors/1000Pop*	*High Purdue MKT*
County Personal Income	-0.018	-0.013
County per Capita Income	-0.001	-0.065
County HPI Growth	-0.038	-0.011
County Labor Participation Rate	-0.023	-0.075
County Unemployment Rate	-0.068	0.040
County Average FICO Score	0.025	-0.121
County Poverty Rate	0.019	0.127
County Crime Rate	-0.008	0.006
County Population Density	0.008	-0.009
County Population	-0.028	-0.013
County Race HHI	-0.023	-0.078
County % Male	-0.122	-0.028
County Average Age	0.117	0.010
County % High Education ($\geq$ College)	0.033	-0.063
County Inequality: Gini Coefficient	0.122	0.087

Table 2: **Effects of the Opioid Crisis on Credit Card Consumer Delinquency: IV Estimates Using the** *"MKT Doctors/1000Pop"* **Instrument**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and 90 days past due status on credit card accounts using 2.5% random sample from anonymized FRBNY Consumer Credit Panel/Equifax (FRBNY CCP). Panel A reports the first-stage IV and Panel B reports second-stage IV estimates. The dependent variable takes a value of 1 if a consumer's credit card balance becomes 90 days or more past due, and zero otherwise. We delete consumers after they become 90+ days past due, i.e., we analyze the first credit card debt delinquency. Subprime (<620) is based on the Equifax Risk Score. The instrument is *MKT Doctors/1000Pop*, the number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. Consumer controls include an indicator for subprime credit score, consumer age ranges, and balances on credit cards, auto loans, and first mortgages. 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 x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

Dependent Variable:	[1] Opioid Death Rate	[2] Top50th_ Opioid Death Rate	[3] Top25th_ Opioid Death Rate	[4] Opioid Prescription Rate	[5] Top50th_ Opioid Prescription Rate	[6] Top25th_ Opioid Prescription Rate
Independent Variables:						
MKT Doctors/1000Pop	1.208***	0.534***	0.562***	0.971***	1.123***	0.766***
	[101.81]	[81.80]	[87.92]	[320.20]	[191.60]	[182.40]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	676,858	676,858	676,858	675,192	676,727	676,727
Adjusted R-squared	0.556	0.392	0.451	0.690	0.527	0.410

Panel B: IV Second Stage

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	90+ Days Past Due Credit Card [%]					
Independent Variables:						
Opioid Death Rate	-0.000593					
	[-0.48]					
Opioid Death Rate × Subprime	0.00785***					
	[14.57]					
Top50th_Opioid Death Rate		-0.00113				
		[-0.41]				
Top50th_Opioid Deaths Rate × Subprime		0.0132***				
		[14.59]				
Top25th_Opioid Death Rate			-0.00186			
			[-0.70]			
Top25th_Opioid Deaths Rate × Subprime			0.0276***			
			[14.57]			
Opioid Prescription Rate				-0.000602		
				[-0.40]		
Opioid Prescription Rate × Subprime				0.0132***		
				[14.91]		
Top50th_Opioid Prescription Rate					-0.00297	
					[-1.05]	
Top50th_Opioid Prescription Rate × Subprime					0.0208***	
					[14.58]	
Top25th_Opioid Prescription Rate						-0.00443*
						[-1.70]
Top25th_Opioid Prescription Rate × Subprime						0.0482***
						[14.57]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	676,858	676,858	676,858	675,192	676,727	676,727
Adjusted R-squared	0.021	0.021	0.020	0.020	0.020	0.019
KP rk Wald F-statistic [Weak-ID]	*4955****	*3196****	*3704****	*4946****	*2725****	*4094****
KP rk LM Statistics [Under-ID]	*9771****	*6335****	*7331****	*8632****	*5410****	*8094****

Table 3: **Effects of the Opioid Crisis on Credit Card Consumer Delinquency: IV Estimates Using the** *"High Purdue MKT '97-'02"* **Instrument**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and 90 days past due status on credit card accounts using 2.5% random sample from anonymized FRBNY Consumer Credit Panel/Equifax (FRBNY CCP). Panel A reports the first-stage IV and Panel B reports second-stage IV estimates. The dependent variable takes a value of 1 if a consumer's credit card balance becomes 90 days or more past due, and zero otherwise. We delete consumers after they become 90+ days past due, i.e., we analyze the first credit card debt delinquency. Subprime (<620) is based on the Equifax Risk Score. The instrument is *High Purdue MKT '97-'02*, indicator for counties in upper 50th percentile of the percentage change in the quantity of OxyContin distributed by Purdue Pharma over 1997-2002. Consumer controls include an indicator for subprime credit score, consumer age ranges, and balances on credit cards, auto loans, and first mortgages. 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 x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	Opioid Death Rate	Top50th_ Opioid Death Rate	Top25th_ Opioid Death Rate	Opioid Prescription Rate	Top50th_ Opioid Prescription Rate	Top25th_ Opioid Prescription Rate
Independent Variables:						
High Purdue MKT	0.0652***	-0.0125***	0.0233***	0.0438***	0.0728***	0.0141***
	[42.68]	[-12.40]	[24.85]	[80.10]	[80.43]	[21.62]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	1,170,188	1,170,185	1,170,185	1,163,987	1,166,983	1,166,983
Adjusted R-squared	0.538	0.308	0.368	0.587	0.460	0.356

Panel B: IV Second Stage

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	90+ Days Past Due Credit Card [%]					
Independent Variables:						
Opioid Death Rate	0.00387					
	[1.17]					
Opioid Death Rate × Subprime	0.0118***					
	[15.13]					
Top50th_Opioid Death Rate		-0.0269				
		[-1.48]				
Top50th_Opioid Deaths Rate × Subprime		0.0156***				
		[15.11]				
Top25th_Opioid Death Rate			0.0103			
			[1.11]			
Top25th_Opioid Deaths Rate × Subprime			0.0442***			
			[15.06]			
Opioid Prescription Rate				0.00617		
				[1.26]		
Opioid Prescription Rate × Subprime				0.0130***		
				[15.23]		
Top50th_Opioid Prescription Rate					0.0562	
					[0.87]	
Top50th_Opioid Prescription Rate × Subprime					0.0244***	
					[12.91]	
Top25th_Opioid Prescription Rate						0.0125
						[1.00]
Top25th_Opioid Prescription Rate × Subprime						0.0753***
						[15.35]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	1,170,188	1,170,185	1,170,185	1,163,987	1,166,983	1,166,983
Adjusted R-squared	0.019	0.007	0.014	0.019	-0.052	0.013
KP rk Wald F-statistic [Weak-ID]	*901.2****	*69.2****	*309.4****	*3139.0****	*5.6****	*179.4****
KP rk LM Statistics [Under-ID]	*1800.0****	*138.3****	*618.8****	*6246.0****	*11.3****	*358.8****

Table 4: **Effects of the Opioid Crisis on Consumer Delinquency for Other Consumer Products: IV Estimates for Auto Loans and Mortgages**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and 90 days past due status on auto loans and first mortgages using 2.5% random sample from anonymized FRBNY Consumer Credit Panel/Equifax (FRBNY CCP). Panel A reports the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument and Panel B reports second-stage IV estimates when using *High Purdue MKT '97-'02* as instrument. The dependent variable takes a value of 1 if a consumer's balance becomes 90 days or more past due, and zero otherwise. We delete consumers after they become 90+ days past due, i.e., we analyze the first debt delinquency. Subprime (<620) is based on the Equifax Risk Score. Consumer controls include an indicator for subprime credit score, consumer age ranges, and balances on credit cards, auto loans, and first mortgages. 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 x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV Estimates Using the *"MKT Doctors/1000Pop"* **Instrument**

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	90+ Days Past Due Auto Loan [%]			90+ Days Past Due Mortgage [%]			90+ Days Past Due Auto Loan [%]			90+ Days Past Due Mortgage [%]		
Independent Variables:												
Opioid Rate	-0.00116			-0.000827			-0.00143			-0.00173		
	[-0.75]			[-0.83]			[-0.92]			[-1.55]		
Opioid Rate × Subprime	0.00418***			0.00143***			0.00491***			0.00181***		
	[9.79]			[3.86]			[7.36]			[2.78]		
Top50th_Opioid Rate		-0.00219			-0.00175			-0.00448			-0.00207	
		[-0.64]			[-0.80]			[-1.34]			[-0.91]	
Top50th_Opioid Rate × Subprime		0.00747***			0.00253***			0.0106***			0.00336***	
		[9.80]			[3.84]			[9.79]			[3.83]	
Top25th_Opioid Rate			-0.00341			-0.00192			-0.00716**			-0.00211
			[-0.99]			[-0.88]			[-2.15]			[-1.03]
Top25th_Opioid Rate × Subprime			0.0143***			0.00487***			0.0229***			0.00756***
			[9.79]			[3.85]			[9.78]			[3.87]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	434,068	434,068	434,068	382,368	382,368	382,368	333,671	433,972	433,972	308,278	382,281	382,281
Adjusted R-squared	0.014	0.014	0.013	0.006	0.006	0.006	0.007	0.013	0.012	0.004	0.006	0.006

Panel B: IV Estimates Using the *"High Purdue MKT '97-'02"* **Instrument**

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	90+ Days Past Due Auto Loan [%]			90+ Days Past Due Mortgage [%]			90+ Days Past Due Auto Loan [%]			90+ Days Past Due Mortgage [%]		
Independent Variables:												
Opioid Rate	-0.00708**			-0.00222			-0.00323			0.000272		
	[-2.10]			[-0.85]			[-0.56]			[0.05]		
Opioid Rate × Subprime	0.00652***			0.00406***			0.00506***			0.00340***		
	[9.55]			[5.81]			[7.48]			[4.16]		
Top50th_Opioid Rate		-0.0659*			0.992			-0.0333**			-0.00947	
		[-1.71]			[0.11]			[-2.28]			[-0.68]	
Top50th_Opioid Rate × Subprime		0.00954***			-0.0300			0.0130***			0.00768***	
		[8.74]			[-0.09]			[9.55]			[5.61]	
Top25th_Opioid Rate			-0.0235**			-0.00629			-0.0208**			-0.00512
			[-2.15]			[-0.90]			[-2.28]			[-0.76]
Top25th_Opioid Rate × Subprime			0.0258***			0.0142***			0.0361***			0.0189***
			[9.54]			[5.81]			[9.61]			[5.99]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	718,789	718,788	718,788	678,777	678,777	678,777	539,302	716,686	716,686	538,493	677,149	677,149
Adjusted R-squared	0.010	-0.099	0.001	0.007	0.000	0.005	0.006	-0.018	0.000	0.005	0.003	0.005

Table 5: **Bank-Level Opioid Exposure and Portfolio Credit Risk: Credit Cards Nonperforming Loans and Charge-Offs**

This table reports bank-level regression estimates from OLS and IV 2SLS regressions explaining the relationship between bank's exposure to the opioid crisis (measured in several ways based on data from CDC and bank branch presence in various markets from FDIC Summary of Deposits) and bank portfolio credit risk when looking at credit card nonperfoming loans and net charge-offs ratios for all banks. Panel A reports the OLS estimates and Panel B reports second-stage IV estimates when using bank's exposure to *High Purdue MKT '97-'02* counties as instrument for bank's exposure to the opioid crisis. All variables are constructed using the FFIEC Call Reports Data. Bank controls include bank capital ratio, liquidity ratio, profitability, bank size, and age. 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, and are calculated as bank's exposure or weighted average of each of these characteristics using as weights the proportions of branches in various counties from FDIC Summary of Deposits. All regressions include Bank and Year-Quarter fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Bank Non-Performing Loans (NPL) and Charge-Offs Ratios for Credit Cards - OLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Credit Cards [%]						Bank Net Charge-Offs - Credit Cards [%]					
Independent Variables:												
Opioid Death Rate	0.1403***						0.1142***					
	[3.29]						[2.52]					
Top50th_Opioid Death Rate		0.291***						0.2346***				
		[6.06]						[3.17]				
Top25th_Opioid Death Rate			0.3279***						0.3283**			
			[3.22]						[2.38]			
Opioid Prescription Rate				0.1195**						0.0412		
				[2.30]						[0.98]		
Top50th_Opioid Prescription Rate					0.4005***						0.2346***	
					[6.17]						[3.17]	
Top25th_Opioid Prescription Rate						-0.2156***						0.3283**
						[-2.92]						[2.38]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	252,622	274,241	274,241	267,873	274,241	274,241	252,670	274,287	274,287	267,919	274,287	274,287
Adjusted R-squared	0.067	0.054	0.054	0.054	0.054	0.053	0.139	0.129	0.129	0.132	0.129	0.129

Panel B: Bank Non-Performing Loans (NPL) and Net Charge-Offs Ratios for Credit Cards Using IV with the *"High Purdue MKT '97-'02"* Instrument

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Credit Cards [%]						Bank Net Charge-Offs - Credit Cards [%]					
Independent Variables:												
Opioid Death Rate	-0.8761***						0.2427					
	[-3.22]						[0.37]					
Top50th_Opioid Death Rate		0.3066***						0.2458***				
		[6.46]						[3.14]				
Top25th_Opioid Death Rate			0.3071***						0.3293**			
			[3.01]						[2.22]			
Opioid Prescription Rate				0.1012***						-0.028		
				[3.22]						[-0.37]		
Top50th_Opioid Prescription Rate					0.3165***						0.1857***	
					[5.32]						[2.98]	
Top25th_Opioid Prescription Rate						-0.2807***						-0.2548***
						[-5.82]						[-4.13]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	245,704	245,704	245,704	245,704	245,704	245,704	245,731	245,731	245,731	245,731	245,731	245,731
Adjusted R-squared	0.285	0.286	0.286	0.285	0.287	0.286	0.083	0.083	0.083	0.083	0.083	0.083

Table 6: **Bank-Level Opioid Exposure and Portfolio Credit Risk: Total Consumer Nonperforming Loans and Charge-Offs**

This table reports bank-level regression estimates from OLS and IV 2SLS regressions explaining the relation between bank's exposure to the opioid crisis (measured in several ways based on data from CDC and bank branch presence in various markets from FDIC Summary of Deposits) and bank portfolio credit risk when looking at total consumer nonperfoming loans and net charge-offs ratios for all banks. Panel A reports the OLS estimates and Panel B reports second-stage IV estimates when using bank's exposure to *High Purdue MKT '97-'02* counties as instrument for bank's exposure to the opioid crisis. All variables are constructed using the FFIEC Call Reports Data. Bank controls include bank capital ratio, liquidity ratio, profitability, bank size, and age. 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, and are calculated as bank's exposure or weighted average of each of these characteristics using as weights the proportions of branches in various counties from FDIC Summary of Deposits. All regressions include Bank and Year-Quarter fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Bank Non-Performing Loans (NPL) and Net Charge-Offs Ratios for Total Consumer Loans using OLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Consumer [%]						Bank Net Charge-Offs - Total Consumer [%]					
Independent Variables:												
Opioid Death Rate	0.219***						0.0023***					
	[3.83]						[4.32]					
Top50th_Opioid Death Rate		0.626***						0.0048***				
		[5.20]						[4.31]				
Top25th_Opioid Death Rate			0.3734**						0.0062***			
			[2.16]						[3.63]			
Opioid Prescription Rate				0.8107***						0.0054***		
				[5.12]						[5.62]		
Top50th_Opioid Prescription Rate					0.6415***						0.0057***	
					[5.05]						[6.12]	
Top25th_Opioid Prescription Rate						0.0343						0.0005
						[0.26]						[0.58]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	202,119	218,213	218,213	213,674	218,213	218,213	202,137	218,229	218,229	218,229	218,229	218,229
Adjusted R-squared	0.259	0.251	0.250	0.253	0.246	0.199	0.124	0.105	0.105	0.115	0.105	0.104

Panel B: Bank Non-Performing Loans (NPL) and Net Charge-Offs Ratios for Consumer Loans Using IV with the *"High Purdue MKT '97-'02"* Instrument

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Consumer [%]						Bank Net Charge-Offs - Consumer [%]					
Independent Variables:												
Opioid Death Rate	1.8882**						0.0076					
	[2.05]						[1.00]					
Top50th_Opioid Death Rate		0.6448***						0.005***				
		[5.47]						[4.69]				
Top25th_Opioid Death Rate			0.3546**						0.0062***			
			[2.00]						[3.63]			
Opioid Prescription Rate				-0.2181**						-0.0009		
				[-2.05]						[-1.00]		
Top50th_Opioid Prescription Rate					0.5192***						0.0055***	
					[4.08]						[6.09]	
Top25th_Opioid Prescription Rate						0.0267						0.0007
						[0.22]						[0.73]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	218,213	218,213	218,213	218,213	218,213	218,213	218,229	218,229	218,229	218,229	218,229	218,229
Adjusted R-squared	0.245	0.259	0.259	0.245	0.246	0.245	0.028	0.029	0.029	0.028	0.029	0.028

Table 7: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: IV Estimates Using the** *"MKT Doctors/1000Pop"* **Instrument**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from 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 offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. The instrument is *MKT Doctors/1000Pop*, the number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

Dependent Variable:	[1] Opioid Death Rate	[2] Top50th_ Opioid Death Rate	[3] Top25th_ Opioid Death Rate	[4] Opioid Prescription Rate	[5] Top50th_ Opioid Prescription Rate	[6] Top25th_ Opioid Prescription Rate
Independent Variables:						
MKT Doctors/1000Pop	0.6771***	0.3601***	0.3697***	0.9039***	1.2160***	1.1190***
	[19.86]	[24.48]	[27.54]	[98.31]	[81.76]	[80.14]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,735	197,735	197,735
Adj R-squared	0.452	0.330	0.331	0.711	0.497	0.487

Panel B: IV Second Stage

Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]	[9] Rate Spread	[10] Ln[Limit]	[11] Rate Spread	[12] Rate Spread
Independent Variables:												
Opioid Death Rate	0.5861***	-0.0773***										
	[3.87]	[-2.68]										
Top50th_Opioid Death Rate			1.1022***	-0.1454***								
			[3.87]	[-2.68]								
Top25th_Opioid Death Rate					1.0733***	-0.1416***						
					[3.88]	[-2.68]						
Opioid Prescription Rate							0.4414***	-0.0576***				
							[3.92]	[-2.67]				
Top50th_Opioid Prescription Rate									0.3281***	-0.0428***		
									[3.92]	[-2.67]		
Top25th_Opioid Prescription Rate											0.3565***	-0.0465***
											[3.92]	[-2.67]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender × Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adj R-squared	0.315	0.155	0.315	0.156	0.319	0.157	0.328	0.162	0.328	0.162	0.327	0.162
KP rk Wald F-statistic [Weak-ID]	*708.2****	*708.2****	*688.6****	*688.6****	*949.4****	*949.4****	*28911****	*28911****	*10454****	*10454****	*11648****	*11648****
KP rk LM Statistics [Under-ID]	*711.7****	*711.7****	*692.1****	*692.1****	*952.8****	*952.8****	*25410****	*25410****	*10009****	*10009****	*11088****	*11088****

Table 8: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: IV Estimates Using the** *"High Purdue MKT '97-'02"* **Instrument**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from 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 offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. The instrument is *High Purdue MKT '97-'02*, indicator for counties in upper 50th percentile of the percentage change in the quantity of OxyContin distributed by Purdue Pharma over 1997-2002. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV First Stage

Dependent Variable:	[1] Opioid Death Rate	[2] Top50th_ Opioid Death Rate	[3] Top25th_ Opioid Death Rate	[4] Opioid Prescription Rate	[5] Top50th_ Opioid Prescription Rate	[6] Top25th_ Opioid Prescription Rate
Independent Variables:						
High Purdue MKT	0.0470***	0.0095***	0.0223***	0.0489***	0.0620***	0.0628***
	[14.21]	[4.65]	[11.78]	[44.91]	[33.95]	[35.23]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	370,960	370,960	370,960	369,432	369,432	369,432
Adjusted R-squared	0.390	0.216	0.215	0.554	0.414	0.391

Panel B: IV Second Stage

Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]	[9] Rate Spread	[10] Ln[Limit]	[11] Rate Spread	[12] Rate Spread
Independent Variables:												
Opioid Death Rate	0.7526***	-0.1470**										
	[2.62]	[-2.22]										
Top50th_Opioid Death Rate			3.7331**	-0.7293**								
			[2.31]	[-2.03]								
Top25th_Opioid Death Rate					1.5840***	-0.3095**						
					[2.61]	[-2.22]						
Opioid Prescription Rate							0.7169***	-0.1418**				
							[2.64]	[-2.25]				
Top50th_Opioid Prescription Rate									0.5651***	-0.1117**		
									[2.63]	[-2.25]		
Top25th_Opioid Prescription Rate											0.5581***	-0.1104**
											[2.63]	[-2.25]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender × Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	370,960	370,960	370,960	370,960	370,960	370,960	369,432	369,432	369,432	369,432	369,432	369,432
Adjusted R-squared	0.265	0.108	0.052	-0.074	0.256	0.102	0.286	0.126	0.284	0.125	0.284	0.125
KP rk Wald F-statistic [Weak-ID]	*211.8****	*211.8****	*21.1****	*21.1****	*154.8****	*154.8****	*2534****	*2534****	*1209****	*1209****	*1579****	*1579****
KP rk LM Statistics [Under-ID]	*213.1****	*213.1****	*21.3****	*21.3****	*155.8****	*155.8****	*2534****	*2534****	*1213****	*1213****	*1583****	*1583****

Table 9: **Additional Identification Tests for the Effects of the Opioid Crisis on Credit Card Supply to Consumers: PSM, Contiguous Counties, Other FEs, Clusters, Adding More Controls**

This table reports consumer-level estimates using additional identification tests for explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and bank credit card terms, rate spread, and credit card limit. Panel A reports marginal average treatment effects using several non-parametric propensity score matching (PSM) techniques, where we match high quartile death and prescription counties to other non-treated counties by year and all county characteristics in our main analyses. Panel B reports results for samples in which we keep high quartile death and prescription counties and their non-treated neighboring counties (contiguous counties). Panels C-E report the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument and additionally clustering errors by offer marketing campaign ID and year-month (Panel C), using State times year-month FEs (Panel D), and when controlling for even more county-level factors including labor participation rate, average credit score, air pollution index, percent of school dropouts, house price index, percent of religious population, politics (ratio of democratic to republican votes in each electoral year, poverty rate, and percent of people with poor health, using data from U.S. Census American Community Surveys, Social Explorer, Federal Housing Finance Agency (FHFA), and MIT Election Lab. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls for regressions include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: PSM Techniques

Panel A1: PSM for *Top25th_Opioid Death Rate*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Rate Spread				Ln(Limit)			
PSM Estimation (with 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 A2: PSM for *Top25th_Opioid Prescription Rate*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Rate Spread				Ln(Limit)			
PSM Estimation (with common support)	**Treated**	**Control**	**Difference**	**t-stat**	**Treated**	**Control**	**Difference**	**t-stat**
1:1 Matching without replacement	17.96	17.38	0.58	17.39***	6.38	6.437	-0.057	-11.06***
1:1 Matching with replacement	17.96	17.32	0.64	5.09***	6.38	6.488	-0.108	-5.39***
Nearest neighbor (n=2)	17.96	17.36	0.6	6.38***	6.38	6.473	-0.093	-6.29***
Nearest neighbor (n=3)	17.96	17.44	0.52	6.25***	6.3829	6.457	-0.0741	-6.00***
Nearest neighbor (n=5)	17.96	17.46	0.5	6.90***	6.3829	6.449	-0.0661	-6.25***

Panel B: Contiguous Counties Only

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]
Independent Variables:								
Opioid Death Rate	1.1360***	-0.1325***						
	[5.27]	[-3.32]						
Top25th_Opioid Death Rate			1.7101***	-0.1994***				
			[5.42]	[-3.36]				
Opioid Prescription Rate					0.2696	-0.0798**		
					[1.49]	[-2.35]		
Top25th_Opioid Prescription Rate							0.1974	-0.0584**
							[1.49]	[-2.35]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	64,589	64,589	64,589	64,589	65,335	65,335	65,335	65,335
Adjusted R-squared	0.256	0.124	0.296	0.146	0.342	0.168	0.342	0.168

Table 9: **Additional Identification Tests for the Effects of the Opioid Crisis on Credit Card Supply to Consumers: PSM, Contiguous Counties, Other FEs, Clusters, Adding More Controls (continued)**

Panel C: Cluster Errors by Marketing Campaign & Year-Month

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5861***	-0.0773***					0.4414***	-0.0576***				
	[3.88]	[-2.69]					[3.94]	[-2.68]				
Top50th_Opioid Rate			1.1022***	-0.1454***					0.3281***	-0.0428***		
			[3.88]	[-2.69]					[3.94]	[-2.68]		
Top25th_Opioid Rate					1.0733***	-0.1416***					0.3565***	-0.0465***
					[3.89]	[-2.69]					[3.94]	[-2.68]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.320	0.161	0.320	0.162	0.324	0.164	0.333	0.169	0.333	0.169	0.333	0.169

Panel D: Use State × Year-Month FE

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5028***	-0.0707***					0.5279***	-0.0736***				
	[4.62]	[-3.52]					[4.67]	[-3.52]				
Top50th_Opioid Rate			1.1582***	-0.1628***					0.3891***	-0.0543***		
			[4.61]	[-3.52]					[4.67]	[-3.52]		
Top25th_Opioid Rate					1.0341***	-0.1453***					0.4238***	-0.0591***
					[4.62]	[-3.52]					[4.67]	[-3.52]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,688	197,688	197,688	197,688	197,688	197,688	197,684	197,684	197,684	197,684	197,684	197,684
Adjusted R-squared	0.304	0.141	0.298	0.138	0.304	0.141	0.312	0.146	0.312	0.146	0.311	0.145

Panel E: Control for Even More Local Market Factors

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.6494***	-0.0829**					0.5220***	-0.0663**				
	[3.63]	[-2.52]					[3.74]	[-2.56]				
Top50th_Opioid Rate			1.3617***	-0.1739**					0.4236***	-0.0538**		
			[3.64]	[-2.52]					[3.74]	[-2.56]		
Top25th_Opioid Rate					1.2066***	-0.1541**					0.4178***	-0.0530**
					[3.67]	[-2.53]					[3.74]	[-2.56]
County Labor Participation Rate	0.5071	-0.3406***	0.6417	-0.3578***	0.3117	-0.3156***	0.8124*	-0.3798***	0.5976	-0.3525***	0.9432**	-0.3964***
	[1.18]	[-4.19]	[1.47]	[-4.35]	[0.73]	[-3.91]	[1.86]	[-4.57]	[1.40]	[-4.35]	[2.10]	[-4.66]
County Avg Credit Score	0.0054**	-0.0004	0.0048**	-0.0003	0.0026	-0.0000	-0.0005	0.0004*	0.0011	0.0002	-0.0013	0.0005**
	[2.32]	[-0.85]	[2.19]	[-0.72]	[1.54]	[-0.03]	[-0.45]	[1.75]	[0.80]	[0.69]	[-1.16]	[2.29]
County Air Pollution	-0.0155***	0.0031***	-0.0431***	0.0066***	-0.0306***	0.0050***	-0.0144**	0.0029***	-0.0157***	0.0031***	-0.0102*	0.0024**
	[-2.65]	[2.86]	[-4.05]	[3.37]	[-3.87]	[3.43]	[-2.52]	[2.78]	[-2.71]	[2.89]	[-1.82]	[2.32]
County Δ HPI	-0.0099**	0.0017**	-0.0067*	0.0013*	0.0035	0.0000	0.0049	-0.0001	0.0044	-0.0001	0.0056*	-0.0002
	[-2.28]	[2.13]	[-1.79]	[1.87]	[1.20]	[0.04]	[1.64]	[-0.23]	[1.50]	[-0.14]	[1.83]	[-0.37]
County % School Dropouts	-1.9034***	-0.0244	-1.1157**	-0.1250	-1.9329***	-0.0207	-2.2203***	0.0164	-2.0089***	-0.0105	-2.2693***	0.0226
	[-4.05]	[-0.28]	[-2.03]	[-1.24]	[-4.14]	[-0.24]	[-4.84]	[0.19]	[-4.35]	[-0.12]	[-4.94]	[0.27]
County % Religious Pop	-0.0262	0.0284	-0.1731*	0.0472**	-0.0511	0.0316	-0.4177***	0.0782***	-0.4418***	0.0813***	-0.5055***	0.0894***
	[-0.22]	[1.24]	[-1.77]	[2.53]	[-0.44]	[1.43]	[-4.68]	[4.56]	[-4.85]	[4.65]	[-5.16]	[4.78]
County Politics	0.0204	-0.0020	0.0113	-0.0009	0.0109	-0.0008	-0.0004	0.0007	0.0143	-0.0012	-0.0088	0.0017
	[1.19]	[-0.63]	[0.75]	[-0.30]	[0.73]	[-0.29]	[-0.03]	[0.27]	[0.93]	[-0.41]	[-0.79]	[0.80]
County Poverty Rate	-0.7311	0.1703	1.0871*	-0.0619	-1.0045	0.2052	1.1000*	-0.0667	1.2535**	-0.0862	0.9618	-0.0491
	[-0.84]	[1.04]	[1.84]	[-0.55]	[-1.09]	[1.19]	[1.90]	[-0.60]	[2.20]	[-0.78]	[1.63]	[-0.43]
County % Poor Health Pop	-0.0098*	0.0019*	-0.0151**	0.0026**	-0.0022	0.0009	0.0000	0.0006	0.0004	0.0006	-0.0006	0.0007
	[-1.83]	[1.80]	[-2.36]	[2.08]	[-0.52]	[1.05]	[0.01]	[0.73]	[0.10]	[0.67]	[-0.13]	[0.81]
Consumer, Other County	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	195,374	195,374	195,374	195,374	195,374	195,374	195,382	195,382	195,382	195,382	195,382	195,382
Adjusted R-squared	0.312	0.153	0.308	0.152	0.316	0.156	0.327	0.162	0.327	0.162	0.327	0.162

Table 10: **Additional Effects of the Opioid Crisis on Credit Card Supply: Probability of Receiving Offers by Consumers Using IV Methodology**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and bank credit card offer probability. Panel A reports the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument and Panel B reports second-stage IV estimates when using *High Purdue MKT '97-'02* as instrument. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV Estimates Using the *"MKT Doctors/1000Pop"* Instrument

Dependent Variable:	[1] Card Offer	[2] Card Offer	[3] Card Offer	[4] Card Offer	[5] Card Offer	[6] Card Offer
Independent Variables:						
Opioid Death Rate	-0.0036***					
	[-2.94]					
Top50th_Opioid Death Rate		-0.0662***				
		[-2.94]				
Top25th_Opioid Death Rate			-0.0709***			
			[-2.94]			
Opioid Prescription Rate				-0.0341***		
				[-3.01]		
Top50th_Opioid Prescription Rate					-0.0276***	
					[-3.01]	
Top25th_Opioid Prescription Rate						-0.0305***
						[-3.01]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	392,130	392,130	392,130	392,116	392,116	392,116
Adjusted R-squared	0.116	0.116	0.116	0.118	0.118	0.118
KP rk Wald F-statistic [Weak-ID]	*1352****	*2212****	*2118****	*21136****	*12744****	*11959****
KP rk LM Statistics [Under-ID]	*1350****	*2335****	*2302****	*19226****	*17824****	*12293****

Panel B: IV Estimates Using the *"High Purdue MKT '97-'02"* Instrument

Dependent Variable:	[1] Card Offer	[2] Card Offer	[3] Card Offer	[4] Card Offer	[5] Card Offer	[6] Card Offer
Independent Variables:						
Opioid Death Rate	-0.0137***					
	[-9.58]					
Top50th_Opioid Death Rate		-0.2107***				
		[-9.54]				
Top25th_Opioid Death Rate			-0.5504***			
			[-8.87]			
Opioid Prescription Rate				-1.5756***		
				[-7.50]		
Top50th_Opioid Prescription Rate					-0.5804***	
					[-9.09]	
Top25th_Opioid Prescription Rate						-1.8102***
						[-5.58]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	752,119	752,119	752,119	749,240	749,240	749,240
Adjusted R-squared	0.114	0.111	-0.036	-0.347	-0.062	-1.463
KP rk Wald F-statistic [Weak-ID]	*2788****	*2141****	*450.3****	*122.8****	*453.7****	*44.48****
KP rk LM Statistics [Under-ID]	*2760****	*2132****	*449.7****	*123.1****	*453.7****	*44.52****

Table 11: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects for Risky vs. Safe Consumers Using IV Methodology**

This table examines how the effects of opioid crisis intensity on bank credit card terms (rate spread and credit card limit) differ by consumer risk (using interactions of consumer risk and opioid intensity): subprime (credit score ¡ 580) in Panel A; past deep delinquency or not in Panel B; past derogatory filings such as foreclosure, collections etc., or not in Panel C; past high utilization ($\geq$ 80%) or not in Panel D. All results report the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls for regressions include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Consumer Risk: Subprime or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.7897***	-0.0982***					0.5526***	-0.0692***				
	[4.59]	[-3.20]					[4.44]	[-3.08]				
Opioid Rate × Subprime	0.1127***	-0.0089**					1.3395***	-0.1112***				
	[5.59]	[-2.49]					[6.35]	[-2.92]				
Top50th_Opioid Rate			1.4185***	-0.1792***					0.3942***	-0.0497***		
			[4.36]	[-3.09]					[4.35]	[-3.03]		
Top50th_Opioid Rate × Subprime			2.7011***	-0.2195***					1.2441***	-0.1045***		
			[5.91]	[-2.70]					[6.53]	[-3.04]		
Top25th_Opioid Rate					1.3626***	-0.1722***					0.4149***	-0.0535***
					[4.38]	[-3.10]					[4.02]	[-2.87]
Top25th_Opioid Rate × Subprime					2.5749***	-0.2067***					1.0974***	-0.0881***
					[5.79]	[-2.60]					[5.83]	[-2.59]
Subprime	-0.5147**	-0.0322	-0.4626**	-0.0342	0.2023	-0.0884***	-0.0795	-0.0641**	0.2173*	-0.0880***	0.6062***	-0.1219***
	[-2.02]	[-0.71]	[-1.97]	[-0.82]	[1.63]	[-3.97]	[-0.49]	[-2.19]	[1.92]	[-4.31]	[9.53]	[-10.62]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.169	0.104	0.170	0.107	0.183	0.111	0.208	0.122	0.207	0.122	0.207	0.122

Panel B: Consumer Risk: Deep Delinquency or Not

	Opioid Death Rate						Opioid Prescription Rate					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.4530***	-0.0737**					0.2738**	-0.0509**				
	(2.86)	(-2.47)					(2.32)	(-2.25)				
Opioid Rate × Deep_Delinq	1.0339***	-0.0549*					0.9174***	-0.0495*				
	(6.28)	(-1.77)					(6.47)	(-1.82)				
Top50th_Opioid Rate			0.7217**	-0.1341**					0.1699*	-0.0356**		
			(2.32)	(-2.28)					(1.92)	(-2.11)		
Top50th_Opioid Rate × Deep_Delinq			1.9280***	-0.0954					0.7592***	-0.0406*		
			(5.98)	(-1.57)					(6.43)	(-1.80)		
Top25th_Opioid Rate					0.7864***	-0.1323**					0.1801*	-0.0387**
					(2.72)	(-2.42)					(1.85)	(-2.08)
Top25th_Opioid Rate × Deep_Delinq					2.1204***	-0.1094*					0.9083***	-0.0486*
					(6.18)	(-1.69)					(6.42)	(-1.80)
Deep_Delinq	-0.4791**	-0.0406	-0.2030	-0.0582*	0.2397***	-0.0797***	0.1208	-0.0723***	0.3903***	-0.0869***	0.5429***	-0.0948***
	(-2.35)	(-1.06)	(-1.22)	(-1.85)	(2.59)	(-4.55)	(1.13)	(-3.53)	(5.81)	(-6.75)	(11.96)	(-10.93)
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.298	0.151	0.302	0.153	0.306	0.155	0.327	0.163	0.327	0.162	0.326	0.162

Table 11: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects for Risky vs. Safe Consumers Using IV (continued)**

Panel C: Consumer Risk: Derogatory Filings: Foreclosure, Collections etc.

	Opioid Death Rate						Opioid Prescription Rate					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.3021*	-0.0682**					0.2738**	-0.0509**				
	(1.89)	(-2.30)					(2.32)	(-2.25)				
Opioid Rate × Other_Derog	1.7356***	-0.0796***					0.9174***	-0.0495*				
	(11.95)	(-2.97)					(6.47)	(-1.82)				
Top50th_Opioid Rate			0.6794**	-0.1331**					0.1699*	-0.0356**		
			(2.24)	(-2.41)					(1.92)	(-2.11)		
Top50th_Opioid Rate × Other_Derog			4.0515***	-0.1923***					0.7592***	-0.0406*		
			(12.00)	(-3.12)					(6.43)	(-1.80)		
Top25th_Opioid Rate					0.3239	-0.1121**					0.1801*	-0.0387**
					(1.12)	(-2.09)					(1.85)	(-2.08)
Top25th_Opioid Rate × Other_Derog					3.9086***	-0.1844***					0.9083***	-0.0486*
					(12.23)	(-3.10)					(6.42)	(-1.80)
Other_Derog	-0.7916***	-0.1022***	-0.7688***	-0.0999***	0.3085***	-0.1524***	1.2149***	-0.1927***	1.2225***	-0.1934***	1.2298***	-0.1942***
	(-4.61)	(-3.22)	(-4.56)	(-3.25)	(3.82)	(-10.17)	(51.12)	(-42.38)	(51.42)	(-42.52)	(51.55)	(-42.57)
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.268	0.149	0.247	0.148	0.280	0.154	0.327	0.163	0.327	0.162	0.326	0.162

Panel D: Consumer Risk: High Utilization or Not

	Opioid Death Rate						Opioid Prescription Rate					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.4671***	-0.0594*					0.3549***	-0.0446**				
	(2.86)	(-1.90)					(3.07)	(-2.02)				
Opioid Rate × High_Util (≥80%)	0.5762***	-0.0811***					0.6747***	-0.0937***				
	(3.72)	(-2.75)					(4.31)	(-3.13)				
Top50th_Opioid Rate			0.8911***	-0.1133*					0.2435***	-0.0304*		
			(2.88)	(-1.93)					(2.85)	(-1.86)		
Top50th_Opioid Rate × High_Util (≥80%)			1.2246***	-0.1725***					0.5718***	-0.0794***		
			(3.69)	(-2.73)					(4.32)	(-3.13)		
Top25th_Opioid Rate					0.8670***	-0.1105**					0.2574***	-0.0319*
					(2.97)	(-1.98)					(2.63)	(-1.70)
Top25th_Opioid Rate × High_Util (≥80%)					1.2508***	-0.1758***					0.5658***	-0.0792***
					(3.81)	(-2.81)					(3.91)	(-2.85)
High_Util (≥80%)	-0.1910	0.0419	-0.1252	0.0326	0.1605*	-0.0078	0.0330	0.0097	0.2195***	-0.0162	0.3740***	-0.0375***
	(-0.99)	(1.14)	(-0.71)	(0.97)	(1.70)	(-0.43)	(0.28)	(0.42)	(2.85)	(-1.10)	(7.87)	(-4.13)
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.314	0.153	0.313	0.154	0.318	0.156	0.329	0.163	0.329	0.163	0.329	0.163

Table 12: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects for Minority Consumers Using IV Methodology**

This table examines how the effects of opioid crisis intensity on bank credit card terms (rate spread and credit card limit) differ by consumer race (using interactions of consumer race/minority and opioid intensity): Minority (non-White) in Panel A; individual Minority groups (Black, Hispanic, Asian, and Other Minority) in Panel B. All results report the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Consumer Minority or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5472***	-0.0637**					0.4016***	-0.0477**				
	[3.34]	[-2.04]					[3.52]	[-2.18]				
Opioid Rate × Minority	0.1835	-0.0640**					0.4347**	-0.1079***				
	[1.23]	[-2.26]					[2.45]	[-3.18]				
Top50th_Opioid Rate			1.0120***	-0.1187**					0.2987***	-0.0354**		
			[3.36]	[-2.07]					[3.51]	[-2.18]		
Top50th_Opioid Rate × Minority			0.5067*	-0.1504***					0.3501**	-0.0877***		
			[1.67]	[-2.60]					[2.40]	[-3.15]		
Top25th_Opioid Rate					1.0073***	-0.1198**					0.3147***	-0.0364**
					[3.43]	[-2.13]					[3.41]	[-2.06]
Top25th_Opioid Rate × Minority					0.4580	-0.1515**					0.4872***	-0.1177***
					[1.36]	[-2.36]					[2.60]	[-3.28]
Minority	0.0672	0.0369	0.0332	0.0356	0.1622**	0.0007	-0.0477	0.0439*	0.0965	0.0082	0.1377***	-0.0033
	[0.42]	[1.20]	[0.25]	[1.39]	[2.20]	[0.05]	[-0.39]	[1.90]	[1.48]	[0.66]	[2.96]	[-0.37]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.316	0.156	0.316	0.156	0.319	0.157	0.328	0.162	0.328	0.162	0.327	0.162

Table 12: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects for Minority Consumers Using IV Methodology (continued)**

Panel B: Decomposition of Consumer Minorities

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5381***	-0.0622*					0.4109***	-0.0480**				
	[3.21]	[-1.95]					[3.59]	[-2.19]				
Opioid Rate × Black	0.5788**	-0.1341***					0.8407***	-0.1659***				
	[2.17]	[-2.63]					[3.50]	[-3.61]				
Opioid Rate × Hispanic	-0.2254	-0.0562					-0.4246	-0.1134				
	[-1.12]	[-1.47]					[-1.09]	[-1.52]				
Opioid Rate × Asian	0.4334	0.1483*					0.7813*	0.1176				
	[0.97]	[1.74]					[1.72]	[1.35]				
Opioid Rate × Other Minority	-1.3245	-0.1451					-1.1006	-0.1360				
	[-1.60]	[-0.92]					[-1.55]	[-1.00]				
Top50th_Opioid Rate			1.0083***	-0.1172**					0.3050***	-0.0356**		
			[3.30]	[-2.01]					[3.57]	[-2.18]		
Top50th_Opioid Rate × Black			1.5065***	-0.3150***					0.6863***	-0.1369***		
			[2.69]	[-2.95]					[3.37]	[-3.51]		
Top50th_Opioid Rate × Hispanic			-0.4928	-0.1089					-0.3203	-0.0999		
			[-1.25]	[-1.45]					[-0.98]	[-1.60]		
Top50th_Opioid Rate × Asian			0.9884	0.2596					0.6735*	0.1041		
			[1.14]	[1.58]					[1.70]	[1.37]		
Top50th_Opioid Rate × Other Minority			-4.5268	-0.9347					-1.1002	-0.1439		
			[-1.13]	[-1.22]					[-1.51]	[-1.03]		
Top25th_Opioid Rate					1.0616***	-0.1206**					0.3169***	-0.0359**
					[3.58]	[-2.13]					[3.42]	[-2.03]
Top25th_Opioid Rate × Black					1.2443**	-0.2832***					0.7913***	-0.1571***
					[2.39]	[-2.85]					[3.44]	[-3.57]
Top25th_Opioid Rate × Hispanic					-0.6994	-0.1177					-0.5037	-0.1802*
					[-1.44]	[-1.27]					[-0.88]	[-1.65]
Top25th_Opioid Rate × Asian					1.4254	0.3654					1.1197*	0.1400
					[1.22]	[1.64]					[1.90]	[1.24]
Top25th_Opioid Rate × Other Minority					-3.6427	-0.4991					-1.2109	-0.1719
					[-1.43]	[-1.03]					[-1.45]	[-1.08]
Black	-0.4059	0.1309**	-0.4749	0.1284**	-0.0286	0.0413	-0.3359*	0.0908***	-0.0916	0.0429**	0.0383	0.0170
	[-1.23]	[2.07]	[-1.64]	[2.32]	[-0.20]	[1.52]	[-1.88]	[2.65]	[-0.80]	[1.96]	[0.49]	[1.14]
Hispanic	0.4822***	0.0055	0.4498***	-0.0016	0.3782***	-0.0273*	0.5295**	0.0285	0.3690***	-0.0097	0.3287***	-0.0166
	[2.61]	[0.16]	[2.97]	[-0.05]	[4.62]	[-1.75]	[2.15]	[0.61]	[3.26]	[-0.45]	[3.71]	[-0.98]
Asian	-0.2454	-0.1270	-0.2016	-0.0812	-0.0561	-0.0404	-0.2853	-0.0529	-0.0105	-0.0102	0.0373	-0.0013
	[-0.59]	[-1.59]	[-0.64]	[-1.35]	[-0.32]	[-1.20]	[-1.12]	[-1.08]	[-0.10]	[-0.51]	[0.47]	[-0.09]
Other Minority	1.4884*	0.1234	1.9906	0.3531	0.9035*	0.0798	0.8813*	0.0728	0.5793*	0.0407	0.3844*	0.0148
	[1.75]	[0.76]	[1.22]	[1.14]	[1.66]	[0.77]	[1.76]	[0.76]	[1.79]	[0.66]	[1.91]	[0.39]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.314	0.153	0.313	0.150	0.316	0.155	0.328	0.162	0.327	0.162	0.327	0.162

Table 13: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects for Age and Gender of Consumers Using IV Methodology**

This table examines how the effects of opioid crisis intensity on bank credit card terms (rate spread and credit card limit) differ by consumer age, gender, and education (using interactions of consumer age, gender, and education and opioid intensity): Young (age <25 years old) in Panel A; Female or not in Panel B. All results report the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Young or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5736***	-0.0747***					0.4397***	-0.0566***				
	[3.85]	[-2.63]					[3.86]	[-2.59]				
Opioid Rate × Age_Less25	0.9558**	-0.1190*					0.5094*	-0.0622				
	[2.55]	[-1.67]					[1.69]	[-1.08]				
Top50th_Opioid Rate			1.0867***	-0.1414***					0.3288***	-0.0423***		
			[3.85]	[-2.64]					[3.84]	[-2.58]		
Top50th_Opioid Rate × Age_Less25			2.3077**	-0.2870					0.3001	-0.0364		
			[2.47]	[-1.62]					[1.45]	[-0.92]		
Top25th_Opioid Rate					1.0552***	-0.1373***					0.3524***	-0.0454**
					[3.85]	[-2.63]					[3.79]	[-2.56]
Top25th_Opioid Rate × Age_Less25					2.0763**	-0.2580					0.4759	-0.0580
					[2.45]	[-1.60]					[1.62]	[-1.03]
Age_Less580	0.1291	-0.0262	0.0202	-0.0128	0.6873***	-0.0959**	0.8780***	-0.1203***	1.0787***	-0.1449***	1.1203***	-0.1499***
	[0.29]	[-0.31]	[0.04]	[-0.14]	[3.00]	[-2.20]	[4.09]	[-2.93]	[9.85]	[-6.92]	[14.45]	[-10.11]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.311	0.153	0.308	0.153	0.314	0.155	0.327	0.162	0.326	0.162	0.326	0.162

Panel B: Female or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.9480***	-0.0844*					1.0715***	-0.1102*				
	[3.77]	[-1.80]					[3.34]	[-1.79]				
Opioid Rate × Female	0.1993	0.0475					0.3472	0.0686				
	[1.00]	[1.28]					[1.22]	[1.25]				
Top50th_Opioid Rate			1.9534***	-0.1839*					0.7987***	-0.0893*		
			[3.51]	[-1.81]					[3.08]	[-1.80]		
Top50th_Opioid Rate × Female			0.9209*	0.1027					0.2288	0.0595		
			[1.74]	[1.06]					[0.97]	[1.31]		
Top25th_Opioid Rate					1.5272***	-0.1463*					0.8668***	-0.1050*
					[3.55]	[-1.82]					[2.84]	[-1.80]
Top25th_Opioid Rate × Female					0.9450**	0.0758					0.4114	0.0705
					[2.17]	[0.93]					[1.35]	[1.22]
Female	-0.3082	-0.0565	-0.5142*	-0.0555	-0.3087**	-0.0201	-0.2954	-0.0510	-0.1542	-0.0310	-0.1418*	-0.0184
	[-1.29]	[-1.26]	[-1.83]	[-1.08]	[-2.56]	[-0.89]	[-1.40]	[-1.26]	[-1.24]	[-1.31]	[-1.72]	[-1.17]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	42,004	42,004	42,004	42,004	42,004	42,004	41,996	41,996	41,996	41,996	41,996	41,996
Adjusted R-squared	0.303	0.173	0.270	0.171	0.303	0.173	0.339	0.176	0.336	0.175	0.333	0.175

Table 14: **Horse Race and Effects of Several Opioid-Related State Laws on Credit Card Supply to Consumers**

This table conducts a horse race among several opioid-related state laws examining their effects on bank credit card terms (rate spread and credit card limit) (using difference-in-difference regressions in which we interact the individual state laws with post-adoption indicators for each law and state, while also including our measures of opioid intensity): horse race among four different state opioid-related laws (opioid prescription limiting law, PDMP Law, Naloxone Law, and Good Samaritan Law) in Panel A; sample splits by Triplicate Prescription Law in Panel B; Medical Marijuana Permitting Law in Panel C. All results report the second-stage IV estimates when using *MKT Doctors/1000Pop* as 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 offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Horse Race Using Four Different Opioid-Related Laws

Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]	[9] Rate Spread	[10] Ln[Limit]	[11] Rate Spread	[12] Ln[Limit]
Independent Variables:												
Post × State Prescription Limiting Law	-0.2043***	0.0277***	-0.0832**	0.0112*	-0.0759**	0.0102*	-0.0129	0.0015	-0.0239	0.0030	-0.0142	0.0017
	[-3.54]	[2.64]	[-2.56]	[1.92]	[-2.42]	[1.81]	[-0.47]	[0.32]	[-0.88]	[0.62]	[-0.52]	[0.35]
Post × State PDMP Law	-0.1879***	0.0456***	-0.1263***	0.0372***	-0.1135**	0.0354***	-0.0143	0.0217***	-0.0121	0.0215***	-0.0094	0.0211**
	[-3.17]	[3.89]	[-2.63]	[3.81]	[-2.47]	[3.75]	[-0.36]	[2.63]	[-0.31]	[2.59]	[-0.24]	[2.54]
Post × State Naloxone Law	0.0967***	0.0098	-0.0003	0.0230***	0.0466	0.0166**	0.1022***	0.0090	0.0976***	0.0096	0.0959***	0.0099
	[3.14]	[1.55]	[-0.01]	[2.96]	[1.41]	[2.49]	[3.33]	[1.42]	[3.18]	[1.53]	[3.13]	[1.56]
Post × State Good Samaritan Law	0.0369	-0.0148**	0.0781**	-0.0204***	0.1450***	-0.0295***	0.0383	-0.0150**	0.0321	-0.0141**	0.0353	-0.0146**
	[1.16]	[-2.41]	[2.23]	[-3.04]	[3.15]	[-3.41]	[1.21]	[-2.44]	[1.02]	[-2.32]	[1.12]	[-2.38]
Opioid Death Rate	0.4573***	-0.0626***										
	[3.65]	[-2.71]										
Top50th_Opioid Death Rate			1.0007***	-0.1369***								
			[3.65]	[-2.71]								
Top25th_Opioid Death Rate					0.9479***	-0.1297***						
					[3.66]	[-2.71]						
Opioid Prescription Rate							0.4135***	-0.0559***				
							[3.69]	[-2.69]				
Top50th_Opioid Prescription Rate									0.3062***	-0.0414***		
									[3.69]	[-2.69]		
Top25th_Opioid Prescription Rate											0.3353***	-0.0453***
											[3.69]	[-2.69]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.321	0.158	0.317	0.157	0.321	0.158	0.328	0.163	0.328	0.162	0.327	0.162

Panel B: Splits by Triplicate Prescription Law

	State Triplicate Prescription Law [Time Invariant]							
	NO		YES		NO		YES	
Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]
Independent Variables:								
Opioid Death Rate	0.8874***	-0.0976**	0.1927	-0.0561				
	[3.45]	[-2.11]	[0.93]	[-1.49]				
Opioid Prescription Rate					0.4843***	-0.0532**	0.2803	-0.0812
					[3.65]	[-2.16]	[0.91]	[-1.44]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	138,703	138,703	58,782	58,782	138,716	138,716	58,766	58,766
Adjusted R-squared	0.293	0.147	0.310	0.146	0.331	0.164	0.310	0.147

Table 14: **Horse Race and Effects of Several Opioid-Related State Laws on Credit Card Supply to Consumers (continued)**

Panel C: Splits by Medical Marijuana Permitting Law

	Medical Marijuana Permitting Law [Time Invariant]							
	YES		NO		YES		NO	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]
Independent Variables:								
Opioid Death Rate	0.4868***	-0.0668***	-0.1965	0.0158				
	[4.10]	[-2.99]	[-0.34]	[0.15]				
Opioid Prescription Rate					0.6170***	-0.0848***	-0.0544	0.0067
					[4.12]	[-3.00]	[-0.29]	[0.20]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	133,480	133,480	64,025	64,025	133,473	133,473	64,028	64,028
Adjusted R-squared	0.305	0.147	0.346	0.170	0.314	0.153	0.348	0.171

Appendix: Supplementary Materials and Analyses

Table A1: **Variable Descriptions and Additional Summary Statistics**

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 FBRNY 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.

Panel A: Definitions and Sources for Variables Used in All Analyses

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
Top50th_Opioid Death Rate	Indicator for high total opioid death rate in the county in the top 50th percentile 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
Top25th_Opioid Death Rate	Indicator for high total opioid death rate in the county in the top 25th percentile 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
Top50th_Opioid Prescription Rate	Indicator for high prescription opioid death rate in the county in the top 50th percentile 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
Top25th_Opioid Prescription Rate	Indicator for high prescription opioid death rate in the county in the top 25th percentile 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 (≥ 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 Descriptions (continued)

Panel B: Definitions and Sources for Variables Specific to the CCP-Based Analysis

Variable	Definition	Source
Key Dependent Variables		
90+ Days Past Due: Credit Card	Indicator of consumers with bankcard balance listed as 90 days and 120 days past due.	FRBNY CCP
90+ Days Past Due: Auto Loan	Indicator of consumers with auto loans listed as 90 days and 120 days past due.	FRBNY CCP
90+ Days Past Due: First Mortgage	Indicator of consumers with first mortgages listed as 90 days and 120 days past due.	FRBNY CCP
Consumer Characteristics		
Equifax Risk Score	Equifax Consumer Risk Score, valid range is 280-850.	FRBNY CCP
Subprime	Indicators of borrowers with risk scores less than 620.	FRBNY CCP
Credit Score_Less580	Equifax Consumer Risk Score range: less than 580 or 300-580.	FRBNY CCP
Credit Score_580_660	Equifax Consumer Risk Score range: 580-660.	FRBNY CCP
Credit Score_660_720	Equifax Consumer Risk Score range: 660-720.	FRBNY CCP
Credit Score_720_800	Equifax Consumer Risk Score range: 720-800.	FRBNY CCP
Credit Score_800plus	Equifax Consumer Risk Score range: greater or equal to 800.	FRBNY CCP
Consumer Age	Consumer age, between 18 and 84.	FRBNY CCP
Age_Less25	Consumer age below 25.	FRBNY CCP
Age_25to44	Consumer age range 25 to 44.	FRBNY CCP
Age_45to64	Consumer age range 45 to 64.	FRBNY CCP
Age_65plus	Consumer age 65 and above.	FRBNY CCP
Ln(Credit Card Balance(000$))	Natural log of bankcard balance listed as current in 000$ for those with positive balances lagged 1 year.	FRBNY CCP
Ln(Auto Loan Balance(000$))	Natural log of auto balance listed as current in 000$ for those with auto loans lagged 1 year.	FRBNY CCP
Ln(First Mortgage Balance(000$))	Natural log of first mortgage balance listed as current in 000$ for those who hold them lagged 1 year.	FRBNY CCP
Consumers with First Mortgages	Indicator for consumers with positive first mortgages.	FRBNY CCP

Table A1: Variable Descriptions (continued)

Panel C: Definitions and Sources for Variables Specific to the FFIEC Call Reports - Based Analysis

Variable	Definition	Source
Key Dependent Variables		
NPL Credit Cards	Non-performing credit cards and similar loans [RCONB576 + RCONB577]/Total Assets [RCON2170].	FFIEC Call Reports
NPL Other Consumer	Non-performing individual and similar loans [RCONK217+RCONK218]/Total Assets [RCON2170]	FFIEC Call Reports
NPL Unsecured Consumer	(Non-performing credit card loans [RCONB576+RCONB577] plus non-performing other unsecured consumer loans [RCONK217+RCONK218])/Total Assets [RCON2170].	FFIEC Call Reports
NPL Secured Consumer	(Non-performing auto loans [RCONK214+RCONK215] plus non-performing residential real estate loans [RCON5399+RCON5400+RCONC237+RCONC229+RCONC239 +RCONC230])/Total Assets [RCON2170].	FFIEC Call Reports
NPL Total Consumer	Sum of non-performing consumer loans in the unsecured and secured segments (NPL Unsecured Consumer + NPL Secured Consumer).	FFIEC Call Reports
Net Charge-Offs Credit Cards	Credit card charge-offs [RIADB514-RIADB515]/Total Assets [RCON2170].	FFIEC Call Reports
Net Charge-Offs Other Consumer	Other consumer loan charge-offs [RIADB516-RIADB517] for years prior to 2011; [RIADK205-RIADK206] for years 2011 and on/Total Assets [RCON2170].	FFIEC Call Reports
Net Charge-Offs Unsecured Consumer	(Credit card charge-offs [RIADB514-RIADB515] + Other consumer loan charge-offs [(RIADB516-RIADB517] for years prior to 2011; [RIADK205-RIADK206] for years 2011 and on)])/Total Assets [RCON2170].	FFIEC Call Reports
Net Charge-Offs Secured Consumer	(Residential real estate loan charge-offs [(RIAD5411-RIAD5412)+(RIADC234-RIADC235)+(RIADC217-RIADC218)] + Auto loan charge-offs [RIADK129-RIADK133])/Total Assets [RCON2170].	FFIEC Call Reports
Net Charge-Offs Total Consumer	Sum of net charge-offs consumer loans in the unsecured and secured segments (Net Charge-Offs Unsecured Consumer + Net Charge-Offs Secured Consumer).	FFIEC Call Reports
Bank Characteristics		
Tier1 Capital	Tier 1 Capital, [RCON7206] (2001-03-31 to 2014-12-31); [RCOA7206] (starting 2014).	FFIEC Call Reports
Liquidity	(Cash [RCON0010] + Federal Funds Repo Liabilities [RCFDB993 + RCFDB995] + Trading Assets. [RCON3545] + Total Securities [RCON1773 + RCON1754])/Total Assets.	FFIEC Call Reports
Profitability	Net Income [RIAD4340]/Total Assets [RCON2170].	FFIEC Call Reports
Bank Size	Log of total assets [RCON2170].	FFIEC Call Reports
Bank Age	Age of the bank (years) computed as Reporting Date [RSSD9999] - Date of Opening [RSSD9950].	FFIEC Call Reports

Table A1: Variable Descriptions (continued)

Panel D: Definitions and Sources for Variables Specific to the Mintel/TransUnion - Based Analysis

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 & Loan Characteristics		
Consumer Credit Score	VantageScore 3.0, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_Less580	VantageScore 3.0 range: less than 580 or 300-580, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_580_660	VantageScore 3.0 range: 580-660, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_660_720	VantageScore 3.0 range: 660-720, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_720_800	VantageScore 3.0 range: 720-800, as of 2-3 months prior to the offer.	Mintel/TransUnion Match File
Credit Score_800plus	VantageScore 3.0 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 (≥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	Consume 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: **Effects of the Opioid Crisis on Consumer Credit Card Delinquency: IV Regression Estimates (All Controls Shown)**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and 90 days past due status on credit card accounts using 2.5% random sample from anonymized FRBNY Consumer Credit Panel/Equifax (FRBNY CCP). Panel A reports the first-stage IV and Panel B reports second-stage IV estimates. The dependent variable takes a value of 1 if a consumer's credit card balance becomes 90 days or more past due, and zero otherwise. We delete consumers after they become 90+ days past due, i.e., we analyze the first credit card debt delinquency. Subprime (<620) is based on the Equifax Risk Score. The instrument is *MKT Doctors/1000Pop*, the number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. Consumer controls include an indicator for subprime credit score, consumer age ranges, and balances on credit cards, auto loans, and first mortgages. 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 x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Effects on Consumer Credit Card Delinquency: IV First Stage

Dependent Variable:	[1] Opioid Death Rate	[2] Top50th_ Opioid Death Rate	[3] Top25th_ Opioid Death Rate	[4] Opioid Prescription Rate	[5] Top50th_ Opioid Prescription Rate	[6] Top25th_ Opioid Prescription Rate
Independent Variables:						
MKT Doctors/1000Pop	1.208***	0.534***	0.562***	0.971***	1.123***	0.766***
	[101.81]	[81.80]	[87.92]	[320.20]	[191.60]	[182.40]
Consumer Characteristics						
Age_25to44	-0.00773**	-0.00157	-0.00692***	-0.000840	0.00457**	0.0000793
	[-2.06]	[-0.76]	[-3.41]	[-0.87]	[2.46]	[0.06]
Age_45to64	-0.00925**	0.0000314	-0.00632***	0.00101	0.00792***	0.00163
	[-2.43]	[0.01]	[-3.09]	[1.04]	[4.22]	[1.21]
Age_65plus	0.00245	0.000461	-0.000917	0.00583***	0.0131***	0.00361***
	[0.63]	[0.22]	[-0.44]	[5.92]	[6.88]	[2.65]
Subprime	-0.0102***	-0.00338*	-0.000772	-0.00185**	-0.00241	-0.00419***
	[-3.04]	[-1.84]	[-0.43]	[-2.16]	[-1.46]	[-3.54]
Ln[Credit Card Balance]	0.000552	0.000557**	0.0000493	-0.000234*	-0.000451*	-0.000551***
	[1.17]	[2.14]	[0.19]	[-1.93]	[-1.93]	[-3.29]
Ln[Auto Balance]	0.000403***	0.0000882	0.000242***	0.000260***	0.000349***	0.0000318
	[4.04]	[1.61]	[4.51]	[10.21]	[7.09]	[0.90]
Ln[First Mortgage Balance]	0.000273***	-0.0000179	0.000102**	0.000146***	0.0000424	0.0000713**
	[3.07]	[-0.37]	[2.13]	[6.44]	[0.97]	[2.27]
County Characteristics						
Ln[County Income]	0.324***	0.405***	-0.0585***	-0.205***	-0.472***	-0.550***
	[32.14]	[73.04]	[-10.78]	[-79.63]	[-94.91]	[-154.30]
County Unemployment Rate	0.00593***	-0.0238***	0.00589***	0.0123***	0.00232***	-0.00956***
	[5.93]	[-43.24]	[10.95]	[48.22]	[4.69]	[-27.05]
County Bank HHI	0.325***	0.120***	0.130***	0.102***	0.136***	-0.0440***
	[37.75]	[25.34]	[27.99]	[46.15]	[32.02]	[-14.41]
County Population Density	-0.0000193***	-0.00000143***	-0.0000117***	0.00000134***	0.00000544***	0.00000362***
	[-115.22]	[-15.57]	[-129.15]	[31.28]	[65.71]	[61.04]
County % Male	-5.698***	1.125***	-2.328***	0.304***	-0.493***	1.767***
	[-54.47]	[19.55]	[-41.32]	[11.37]	[-9.52]	[47.67]
County Race HHI	-0.218***	-0.0106***	-0.0987***	-0.116***	-0.206***	0.0272***
	[-31.92]	[-2.83]	[-26.84]	[-66.22]	[-61.19]	[11.28]
County % Age_25_44	4.543***	0.865***	2.359***	-0.797***	0.121***	0.373***
	[91.68]	[31.74]	[88.38]	[-62.96]	[4.94]	[21.31]
County % Age_45_64	2.017***	-0.478***	1.577***	0.804***	1.422***	2.652***
	[32.27]	[-13.89]	[46.85]	[50.38]	[46.10]	[120.03]
County % Age_65plus	2.364***	0.239***	1.498***	1.291***	3.423***	1.647***
	[59.02]	[10.84]	[69.40]	[126.09]	[173.04]	[116.20]
County % High Education [$\geq$ College]	-3.983***	-1.990***	-0.953***	-0.611***	-0.885***	0.580***
	[-104.53]	[-94.94]	[-46.43]	[-62.73]	[-47.04]	[43.04]
County Inequality: Gini Coefficient	2.409***	0.697***	0.395***	-0.222***	-1.122***	0.520***
	[68.77]	[36.16]	[20.95]	[-24.75]	[-64.90]	[41.94]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	696,417	696,417	696,417	696,432	696,382	696,382
R-squared	0.556	0.392	0.451	0.690	0.527	0.410

Table A2: **Effects of the Opioid Crisis on Credit Consumer Card Delinquency: IV Regression Estimates (All Controls Shown) (continued)**

Panel B: Effects on Consumer Credit Card Delinquency: IV Second Stage

	Opioid Death Rate			Opioid Prescription Rate		
	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	90+ Days Past Due Credit Card [%]					
Independent Variables:						
Opioid Rate	-0.000593			-0.000602		
	(-0.48)			(-0.40)		
Opioid Rate × Subprime	0.00785***			0.0132***		
	(14.57)			(14.91)		
Top50th_Opioid Rate		-0.00113			-0.00297	
		(-0.41)			(-1.05)	
Top50th_Opioid Rate × Subprime		0.0132***			0.0208***	
		(14.59)			(14.58)	
Top25th_Opioid Rate			-0.00186			-0.00443*
			(-0.70)			(-1.70)
Top25th_Opioid Rate × Subprime			0.0276***			0.0482***
			(14.57)			(14.57)
Subprime	0.0422***	0.0420***	0.0424***	0.0409***	0.0424***	0.0431***
	(75.55)	(74.16)	(77.68)	(73.54)	(77.32)	(82.64)
Consumer Characteristics						
Age_25to44	-0.00402***	-0.00402***	-0.00403***	-0.00395***	-0.00402***	-0.00402***
	(-7.83)	(-7.83)	(-7.85)	(-7.77)	(-7.84)	(-7.83)
Age_45to64	-0.00577***	-0.00577***	-0.00579***	-0.00567***	-0.00579***	-0.00584***
	(-11.16)	(-11.17)	(-11.20)	(-11.06)	(-11.20)	(-11.29)
Age_65plus	-0.00601***	-0.00602***	-0.00604***	-0.00593***	-0.00601***	-0.00606***
	(-11.50)	(-11.51)	(-11.55)	(-11.45)	(-11.48)	(-11.57)
Ln(Credit Card Balance)	0.00113***	0.00113***	0.00113***	0.00114***	0.00114***	0.00114***
	(19.09)	(19.09)	(19.08)	(19.60)	(19.23)	(19.24)
Ln(Auto Balance)	0.0000783***	0.0000779***	0.0000786***	0.0000809***	0.0000779***	0.0000802***
	(6.33)	(6.31)	(6.35)	(6.62)	(6.30)	(6.49)
Ln(First Mortgage Balance)	-0.000140***	-0.000140***	-0.000142***	-0.000142***	-0.000143***	-0.000146***
	(-12.76)	(-12.71)	(-12.94)	(-13.07)	(-13.03)	(-13.28)
County Characteristics						
Ln(County Income)	-0.00417***	0.00741	-0.00435***	-0.00425***	-0.00207	-0.00321**
	(-3.07)	[0.84]	(-3.50)	(-3.42)	(-0.94)	(-2.55)
County Unemployment Rate	0.0000155	-0.00107***	0.0000263	-0.0000213	-0.0000459	0.0000146
	(0.12)	[-2.64]	(0.21)	(-0.17)	(-0.35)	(0.12)
County Bank HHI	-0.000658	-0.00233	-0.000658	-0.00110	-0.000245	0.0000412
	(-0.58)	[-0.45]	(-0.59)	(-1.03)	(-0.20)	(0.04)
County Population Density	1.90e-08	0.00000332	1.73e-08	1.83e-08	1.78e-08	-6.87e-09
	(0.58)	[0.99]	(0.45)	(0.89)	(0.85)	(-0.27)
County % Male	0.0256*	0.000	0.0245	0.0296**	0.0310**	0.0233*
	(1.67)	[.]	(1.64)	(2.30)	(2.33)	(1.75)
County Race HHI	0.000840	-0.0284*	0.000921	0.000530	0.000616	0.00122
	(0.93)	[-1.90]	(1.02)	(0.61)	(0.56)	(1.42)
County % Age_25_44	-0.00322	-0.0590	-0.00291	-0.00287	-0.00386	0.00776
	(-0.40)	[-0.95]	(-0.34)	(-0.46)	(-0.62)	(0.84)
County % Age_45_64	0.00931	-0.0160	0.0103	0.00996	0.000691	0.00627
	(1.16)	[-0.14]	(1.19)	(1.29)	(0.06)	(0.78)
County % Age_65plus	-0.00518	-0.0743	-0.00534	-0.00439	-0.00772	0.000870
	(-0.88)	[-1.02]	(-0.82)	(-0.81)	(-1.44)	(0.10)
County % High Education ($\geq$ College)	-0.00413	0.0206	-0.00340	-0.00418	-0.0109	-0.0104*
	(-0.58)	[0.48]	(-0.61)	(-0.86)	(-1.21)	(-1.89)
County Inequality: Gini Coefficient	0.0124**	-0.00280	0.0119**	0.0132***	0.0139***	0.00935**
	(2.19)	[-0.08]	(2.55)	(3.09)	(3.18)	(2.17)
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	676,858	676,858	676,858	675,192	676,727	676,727
Adjusted R-squared	0.021	0.021	0.020	0.020	0.020	0.019

Table A3: **Effects of the Opioid Crisis on Consumer Credit Card Delinquency: OLS Regression Estimates and Starting the Sample Earlier**

This table reports consumer-level regression estimates explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and 90 days past due status on credit card accounts using 2.5% random sample from anonymized FRBNY Consumer Credit Panel/Equifax (FRBNY CCP). Panel A reports OLS regression estimates, while Panel B reports IV estimates when starting teh sample earlier in 2007 and using the *"High Purdue MKT '97-'02"* as an instrument. The dependent variable takes a value of 1 if a consumer's credit card balance becomes 90 days or more past due, and zero otherwise. We delete consumers after they become 90+ days past due, i.e., we analyze the first credit card debt delinquency. Subprime (<620) is based on the Equifax Risk Score. Consumer controls include an indicator for subprime credit score, consumer age ranges, and balances on credit cards, auto loans, and first mortgages. 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 x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: OLS Regression Estimates

	[1]	[2]
Dependent Variable:	90+ Days Past Due Credit Card [%]	
Independent Variables:		
Opioid Death Rate	-0.000543***	
	[-4.14]	
Opioid Death Rate × Subprime	0.00454***	
	[15.55]	
Opioid Prescription Rate		-0.000998***
		[-2.77]
Opioid Prescription Rate × Subprime		0.0104***
		[21.55]
Subprime	0.0453***	0.0414***
	[125.85]	[107.12]
Consumer, County Controls	YES	YES
State × Year FE	YES	YES
Observations	1,170,188	1,163,990
Adjusted R-squared	0.022	0.021

Panel B: IV Estimates Starting the Sample Earlier in 2007

	Opioid Death Rate			Opioid Prescription Rate		
	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	90+ Days Past Due Credit Card [%]			90+ Days Past Due Credit Card [%]		
Independent Variables:						
Opioid Rate	0.00534			0.00717		
	[1.42]			[1.54]		
Opioid Rate × Subprime	0.0159***			0.0159***		
	[19.66]			[19.86]		
Top50th_Opioid Rate		-0.0610*			0.0245	
		[-1.70]			[0.98]	
Top50th_Opioid Rate × Subprime		0.0189***			0.0295***	
		[18.85]			[19.25]	
Top25th_Opioid Rate			0.0227			0.0125
			[1.48]			[0.80]
Top25th_Opioid Rate × Subprime			0.0552***			0.0876***
			[19.58]			[19.87]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State × Year FE	YES	YES	YES	YES	YES	YES
Observations	1,411,024	1,411,024	1,411,024	1,407,056	1,406,750	1,406,750
Adjusted R-squared	0.020	-0.044	0.007	0.023	0.010	0.014

Table A4: **Bank-Level Opioid Exposure and Portfolio Credit Risk: Credit Cards Nonperforming Loans and Charge-Offs for *Single-County Banks***

This table reports bank-level regression estimates from OLS and IV 2SLS regressions explaining the relationship between bank's exposure to the opioid crisis (measured several ways based on data from CDC and bank branch presence in various markets from FDIC Summary of Deposits) and bank portfolio credit risk when looking at credit cards nonperfoming loans and net charge-offs ratios for single-county operating banks. Panel A reports the OLS estimates and Panel B reports second-stage IV estimates when using bank's exposure to *High Purdue MKT '97-'02* counties as instrument for bank's exposure to the opioid crisis. All variables are constructed using the FFIEC Call Reports Data for analyzing bank loan portfolio. Bank controls include bank capital ratio, liquidity ratio, profitability, bank size, and age. 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, and are calculated as bank's exposure or weighted average of each of these characteristics using as weights the proportions of branches in various counties from FDIC Summary of Deposits. All regressions include Bank and Year-Quarter fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Bank Non-Performing Loans (NPL) and Charge-Offs Ratios for Credit Cards - OLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Credit Cards [%]						Bank Net Charge-Offs - Credit Cards [%]					
Independent Variables:												
Opioid Death Rate	0.6983***						0.6094***					
	[3.91]						[3.41]					
Top50th_Opioid Death Rate		1.2869***						1.1601***				
		[6.58]						[3.83]				
Top25th_Opioid Death Rate			1.2997***						1.4761***			
			[3.13]						[2.49]			
Opioid Prescription Rate				0.8389***						0.6853		
				[4.38]						[1.03]		
Top50th_Opioid Prescription Rate					1.8743***						1.1354***	
					[6.96]						[3.55]	
Top25th_Opioid Prescription Rate						-0.2032						1.467**
						[-0.53]						[2.28]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	47,792	59,552	59,552	55,340	59,552	59,552	47,795	59,553	59,553	52,028	52,020	52,020
Adjusted R-squared	0.141	0.130	0.130	0.132	0.134	0.130	0.168	0.156	0.156	0.161	0.160	0.155

Panel B: Bank Non-Performing Loans (NPL) and Net Charge-Offs Ratios for Credit Cards using IV with the *"High Purdue MKT '97-'02"* Instrument

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Credit Cards [%]						Bank Net Charge-Offs - Credit Cards [%]					
Independent Variables:												
Opioid Death Rate	-0.2393						0.6079***					
	[-0.94]						[4.14]					
Top50th_Opioid Death Rate		1.254***						1.4336***				
		[6.41]						[4.64]				
Top25th_Opioid Death Rate			1.174***						-0.4181			
			[2.82]						[-1.15]			
Opioid Prescription Rate				0.2462***						1.3316***		
				[3.06]						[4.06]		
Top50th_Opioid Prescription Rate					1.6738***						-0.5987*	
					[6.63]						[-1.74]	
Top25th_Opioid Prescription Rate						-0.5017**						-0.0373
						[-2.09]						[-0.22]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	59,552	52,023	52,023	52,031	52,023	52,023	55,341	59,553	59,553	52,020	52,020	52,028
Adjusted R-squared	0.365	0.369	0.371	0.366	0.373	0.367	0.075	0.075	0.076	0.075	0.076	0.075

Table A5: **Bank-Level Opioid Exposure and Portfolio Credit Risk: Total Consumer Nonperforming Loans and Charge-Offs for *Single-County Banks***

This table reports bank-level regression estimates from OLS and IV 2SLS regressions explaining the relationship between bank's exposure to the opioid crisis (measured several ways based on data from CDC and bank branch presence in various markets from FDIC Summary of Deposits) and bank portfolio credit risk when looking at total consumer nonperfoming loans and net charge-offs ratios for single-county operating banks. Panel A reports the OLS estimates and Panel B reports second-stage IV estimates when using bank's exposure to *High Purdue MKT '97-'02* counties as instrument for bank's exposure to the opioid crisis. All variables are constructed using the FFIEC Call Reports Data for analyzing bank loan portfolio. Bank controls include bank capital ratio, liquidity ratio, profitability, bank size, and age. 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, and are calculated as bank's exposure or weighted average of each of these characteristics using as weights the proportions of branches in various counties from FDIC Summary of Deposits. All regressions include Bank and Year-Quarter fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Bank Non-Performing Loans (NPL) and Net Charge-Offs Ratios for Consumer Loans using OLS

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Consumer [%]						Bank Net Charge-Offs - Consumer [%]					
Independent Variables:												
Opioid Death Rate	3.8899***						0.7017***					
	[4.51]						[3.43]					
Top50th_Opioid Death Rate		8.0226***						1.4065***				
		[6.19]						[3.01]				
Top25th_Opioid Death Rate			10.3041***						1.8614***			
			[5.94]						[2.54]			
Opioid Prescription Rate				9.3102***						1.2746***		
				[4.93]						[4.46]		
Top50th_Opioid Prescription Rate					8.1628***						1.8352***	
					[5.98]						[4.66]	
Top25th_Opioid Prescription Rate						2.8625*						-0.0337
						[1.63]						[3.74]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	37,483	46,207	46,207	43,228	46,207	46,207	37,482	46,204	46,204	43,225	46,204	46,204
Adjusted R-squared	0.339	0.300	0.302	0.315	0.300	0.294	0.178	0.155	0.155	0.173	0.157	0.154

Panel B: Bank Non-Performing Loans (NPL) and Net Charge-Offs Ratios for Consumer Loans using IV with the *"High Purdue MKT '97-'02"* Instrument

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Bank NPL - Consumer [%]						Bank Net Charge-Offs - Consumer [%]					
Independent Variables:												
Opioid Death Rate	2.7939*						0.970					
	[1.73]						[1.29]					
Top50th_Opioid Death Rate		8.2208***						1.4617***				
		[6.33]						[3.21]				
Top25th_Opioid Death Rate			10.34***						1.8625***			
			[5.93]						[2.53]			
Opioid Prescription Rate				-0.3886						-0.012		
				[-1.05]						[-0.06]		
Top50th_Opioid Prescription Rate					9.4443***						1.8010***	
					[6.73]						[4.46]	
Top25th_Opioid Prescription Rate						4.2091**						0.0199
						[2.3]						[0.05]
Bank, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank, Year-Quarter FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	45,672	45,664	45,664	45,672	45,664	45,664	45,669	45,661	45,661	45,669	45,661	45,661
Adjusted R-squared	0.308	0.318	0.321	0.307	0.315	0.310	0.023	0.024	0.024	0.023	0.024	0.023

Table A6: **Effects of the Opioid Crisis on Credit Supply to Consumers: IV Regression Estimates (All Controls Shown)**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from 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 offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. The instrument is *MKT Doctors/1000Pop*, the number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Effects on Credit Card Terms: IV First Stage

Dependent Variable:	[1] Opioid Death Rate	[2] Top50th_ Opioid Death Rate	[3] Top25th_ Opioid Death Rate	[4] Opioid Prescription Rate	[5] Top50th_ Opioid Prescription Rate	[6] Top25th_ Opioid Prescription Rate
Independent Variables:						
MKT Doctors/1000Pop	0.6771***	0.3601***	0.3697***	0.9039***	1.2160***	1.1190***
	[19.86]	[24.48]	[27.54]	[98.31]	[81.76]	[80.14]
Consumer & Loan Characteristics						
Credit Score_Less580	-0.0226***	-0.0049	-0.0124***	0.0011	-0.0021	0.0045
	[-2.90]	[-1.26]	[-3.52]	[0.71]	[-0.60]	[1.43]
Credit Score_660_720	-0.0509***	-0.0105**	-0.0240***	0.0017	-0.0144***	-0.0135***
	[-6.04]	[-2.41]	[-6.15]	[0.96]	[-3.80]	[-3.89]
Credit Score_720_800	-0.0278***	-0.0184***	-0.0260***	-0.0072***	-0.0217***	-0.0100***
	[-3.17]	[-4.06]	[-6.44]	[-3.95]	[-5.50]	[-2.80]
Credit Score_800plus	-0.0414***	-0.0299***	-0.0324***	-0.0146***	-0.0376***	-0.0204***
	[-4.38]	[-6.18]	[-7.50]	[-7.63]	[-8.95]	[-5.42]
Deep_Delinq	0.0084	0.0114***	0.0037	0.0020	0.0083***	0.0136***
	[1.40]	[3.65]	[1.31]	[1.61]	[3.01]	[5.60]
Recent_Delinq	-0.0227***	-0.0033	0.0006	-0.0036**	0.0051	-0.0213***
	[-2.88]	[-0.78]	[0.15]	[-2.16]	[1.37]	[-6.44]
Other_Derogatory	-0.0295***	-0.0143***	-0.0256***	0.0002	-0.0114***	-0.0219***
	[-5.00]	[-4.51]	[-9.20]	[0.17]	[-4.08]	[-8.97]
Bankruptcy_Filer	0.0763***	0.0218***	0.0486***	0.0062***	0.0302***	0.0155***
	[8.37]	[4.78]	[11.74]	[3.42]	[7.61]	[4.18]
High_Util [$\geq$80%]	-0.0100	0.0212***	0.0109**	0.0095***	0.0388***	-0.0030
	[-0.89]	[3.44]	[1.98]	[4.01]	[7.42]	[-0.63]
Ln[1+ No Credit Inquiries]	0.0166***	0.0029	0.0067***	0.0017**	-0.0015	-0.0027*
	[4.83]	[1.59]	[4.09]	[2.34]	[-0.90]	[-1.88]
Has_Prior_Cards	-0.0154*	0.0088**	0.0027	0.0105***	0.0024	0.0159***
	[-1.95]	[2.08]	[0.73]	[6.04]	[0.64]	[4.68]
Age_25to44	0.0035	-0.0084	-0.0088**	-0.0093***	-0.0326***	-0.0250***
	[0.40]	[-1.63]	[-1.97]	[-4.95]	[-7.45]	[-6.20]
Age_45to64	0.0271***	0.0045	0.0167***	0.0071***	-0.0120***	-0.0093**
	[3.03]	[0.88]	[3.69]	[3.71]	[-2.71]	[-2.30]
Age_65plus	0.0361***	0.0080	0.0148***	-0.0043**	-0.0283***	-0.0168***
	[3.71]	[1.45]	[3.08]	[-2.10]	[-6.00]	[-3.89]
Married	-0.0053	0.0013	0.0137***	-0.0067***	-0.0013	0.0036*
	[-1.09]	[0.48]	[5.76]	[-6.34]	[-0.54]	[1.72]
No_Kids	-0.0241***	-0.0045	-0.0056**	-0.0063***	-0.0114***	-0.0126***
	[-4.32]	[-1.49]	[-2.08]	[-5.11]	[-4.20]	[-5.52]

Table A5: **Effects of the Opioid Crisis on Credit Supply to Consumers: IV Regression Estimates (All Controls Shown) (continued)**

Panel A: Effects on Credit Card Terms: IV First Stage (cont.)

Dependent Variable:	[1] Opioid Death Rate	[2] Top50th_ Opioid Death Rate	[3] Top25th_ Opioid Death Rate	[4] Opioid Prescription Rate	[5] Top50th_ Opioid Prescription Rate	[6] Top25th_ Opioid Prescription Rate
Independent Variables (continued):						
White	0.0492***	0.0189***	0.0210***	0.0234***	0.0246***	0.0169***
	[7.98]	[5.44]	[7.45]	[16.49]	[8.28]	[6.53]
Miss_Race	0.0450***	-0.0205***	0.0273***	0.0113***	0.0041	-0.0022
	[4.57]	[-4.22]	[6.54]	[5.94]	[0.96]	[-0.59]
Educ: Some_College	0.0386***	0.0268***	0.0149***	0.0058***	0.0285***	0.0102***
	[6.39]	[7.82]	[4.91]	[4.00]	[9.07]	[3.76]
Educ: College	0.0355***	0.0063*	0.0043	-0.0048***	-0.0155***	-0.0004
	[5.93]	[1.85]	[1.47]	[-3.61]	[-5.27]	[-0.15]
Educ: Post_College	0.0153*	0.0027	0.0080**	-0.0071***	0.0021	0.0027
	[1.87]	[0.61]	[2.05]	[-4.44]	[0.55]	[0.83]
Miss Educ	-0.0281***	0.0322***	-0.0190***	0.0025*	0.0031	0.0263***
	[-3.50]	[8.46]	[-5.57]	[1.75]	[0.90]	[9.03]
Homeowner	-0.0218***	-0.0143***	-0.0132***	0.0050***	0.0066***	-0.0154***
	[-4.91]	[-5.99]	[-6.33]	[5.38]	[3.21]	[-8.43]
Ln[Consumer Income]	-0.0086***	-0.0056***	-0.0117***	-0.0095***	-0.0148***	-0.0129***
	[-3.45]	[-4.29]	[-9.94]	[-17.54]	[-12.56]	[-12.29]
County Characteristics						
Ln[County Income]	0.0518***	0.0333***	0.0338***	-0.0670***	-0.0714***	-0.0924***
	[19.13]	[25.33]	[30.54]	[-105.87]	[-59.30]	[-85.93]
County Unemployment Rate	0.0668***	0.0140***	0.0230***	0.0181***	0.0338***	0.0186***
	[32.42]	[13.59]	[26.63]	[28.62]	[25.75]	[18.98]
County Bank HHI	0.4851***	0.2241***	0.1479***	-0.0356***	-0.0058	-0.0438***
	[27.47]	[23.08]	[15.32]	[-8.03]	[-0.63]	[-4.78]
County Population Density	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000***	0.0000
	[-60.35]	[-43.42]	[-56.74]	[-18.96]	[-6.00]	[1.27]
County Race HHI	-0.1907***	-0.1076***	-0.0962***	-0.1790***	-0.3396***	-0.1802***
	[-20.30]	[-18.39]	[-24.08]	[-64.46]	[-74.38]	[-44.83]
County % Male	-3.9633***	0.5720***	-1.6145***	-1.7377***	-4.7750***	-1.9410***
	[-13.89]	[3.99]	[-12.36]	[-21.62]	[-30.54]	[-15.42]
County % Age_25_44	4.2001***	0.9804***	1.2081***	-0.0167	-0.3541***	1.7126***
	[29.66]	[12.60]	[21.34]	[-0.61]	[-5.69]	[34.00]
County % Age_45_64	3.0614***	0.9531***	0.7412***	0.9836***	1.6762***	1.6239***
	[26.94]	[14.49]	[13.49]	[34.20]	[26.30]	[30.23]
County % Age_65plus	3.0512***	1.3069***	1.8064***	1.0513***	1.5020***	2.0436***
	[33.46]	[21.40]	[38.30]	[47.25]	[33.43]	[43.06]
County % High Education [$\geq$ College]	-0.3975***	-0.0537***	-0.2885***	-0.4786***	-0.7486***	-0.9061***
	[-13.14]	[-3.18]	[-21.44]	[-56.60]	[-45.75]	[-69.68]
County Inequality: Gini Coefficient	1.2801***	0.2724***	-0.2473***	-0.1042***	-0.8000***	0.0658**
	[14.28]	[6.27]	[-6.29]	[-5.38]	[-20.84]	[1.99]
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,735	197,735	197,735
Adjusted R-squared	0.452	0.330	0.331	0.711	0.497	0.487

Table A5: **Effects of the Opioid Crisis on Credit Supply to Consumers: IV Regression Estimates (All Controls Shown) (continued)**

Panel B: Effects on Credit Card Terms: IV Second Stage

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Death Rate	0.5861***	-0.0773***										
	[3.87]	[-2.68]										
Top50th_Opioid Death Rate			1.1022***	-0.1454***								
			[3.87]	[-2.68]								
Top25th_Opioid Death Rate					1.0733***	-0.1416***						
					[3.88]	[-2.68]						
Opioid Prescription Rate							0.4414***	-0.0576***				
							[3.92]	[-2.67]				
Top50th_Opioid Prescription Rate									0.3281***	-0.0428***		
									[3.92]	[-2.67]		
Top25th_Opioid Prescription Rate											0.3565***	-0.0465***
											[3.92]	[-2.67]
Consumer & Loan Characteristics												
Credit Score_Less580	-0.2101***	0.0850***	-0.2180***	0.0860***	-0.2101***	0.0849***	-0.2241***	0.0868***	-0.2229***	0.0866***	-0.2252***	0.0869***
	[-7.08]	[15.04]	[-7.39]	[15.32]	[-7.10]	[15.06]	[-7.68]	[15.54]	[-7.64]	[15.51]	[-7.72]	[15.57]
Credit Score_660_720	-1.9186***	0.2278***	-1.9369***	0.2302***	-1.9227***	0.2283***	-1.9501***	0.2319***	-1.9447***	0.2312***	-1.9446***	0.2312***
	[-56.72]	[35.35]	[-58.65]	[36.62]	[-57.41]	[35.74]	[-59.93]	[37.24]	[-59.69]	[37.08]	[-59.67]	[37.07]
Credit Score_720_800	-3.7277***	0.3951***	-3.7238***	0.3946***	-3.7161***	0.3935***	-3.7404***	0.3967***	-3.7365***	0.3962***	-3.7400***	0.3967***
	[-108.12]	[60.16]	[-107.52]	[59.85]	[-106.46]	[59.11]	[-110.43]	[61.20]	[-110.14]	[61.02]	[-110.37]	[61.17]
Credit Score_800plus	-4.4021***	0.5237***	-4.3934***	0.5226***	-4.3916***	0.5224***	-4.4198***	0.5261***	-4.4139***	0.5253***	-4.4190***	0.5260***
	[-118.82]	[74.22]	[-117.08]	[73.17]	[-117.04]	[72.98]	[-122.20]	[76.00]	[-121.65]	[75.64]	[-122.10]	[75.95]
Deep_Delinq	0.7917***	-0.1080***	0.7840***	-0.1070***	0.7927***	-0.1081***	0.7966***	-0.1086***	0.7947***	-0.1084***	0.7926***	-0.1081***
	[33.65]	[-24.10]	[33.08]	[-23.72]	[33.81]	[-24.18]	[34.21]	[-24.38]	[34.13]	[-24.32]	[34.00]	[-24.24]
Recent_Delinq	0.0479	-0.1012***	0.0382	-0.0999***	0.0340	-0.0994***	0.0362	-0.0996***	0.0329	-0.0992***	0.0422	-0.1004***
	[1.49]	[-16.50]	[1.19]	[-16.39]	[1.07]	[-16.32]	[1.14]	[-16.42]	[1.04]	[-16.34]	[1.33]	[-16.51]
Other_Derogatory	1.2335***	-0.1949***	1.2320***	-0.1947***	1.2436***	-0.1963***	1.2163***	-0.1927***	1.2202***	-0.1932***	1.2242***	-0.1937***
	[50.58]	[-41.96]	[50.65]	[-42.06]	[49.90]	[-41.28]	[51.20]	[-42.38]	[51.32]	[-42.45]	[51.34]	[-42.46]
Bankruptcy_Filer	0.2321***	0.0426***	0.2528***	0.0399***	0.2247***	0.0436***	0.2735***	0.0370***	0.2663***	0.0380***	0.2707***	0.0374***
	[6.35]	[6.12]	[7.18]	[5.95]	[6.06]	[6.16]	[7.97]	[5.64]	[7.74]	[5.77]	[7.88]	[5.69]
High_Util [≥80%]	0.2733***	-0.0173*	0.2440***	-0.0134	0.2557***	-0.0149*	0.2634***	-0.0160*	0.2549***	-0.0149*	0.2687***	-0.0167*
	[5.89]	[-1.95]	[5.21]	[-1.50]	[5.51]	[-1.69]	[5.73]	[-1.82]	[5.53]	[-1.68]	[5.84]	[-1.89]
Ln[1+ No Credit Inquiries]	0.2723***	-0.0187***	0.2788***	-0.0196***	0.2748***	-0.0191***	0.2813***	-0.0199***	0.2826***	-0.0201***	0.2830***	-0.0201***
	[19.33]	[-6.98]	[20.06]	[-7.41]	[19.70]	[-7.17]	[20.46]	[-7.57]	[20.55]	[-7.63]	[20.58]	[-7.65]
Has_Prior_Cards	-0.8292***	0.1391***	-0.8479***	0.1416***	-0.8411***	0.1407***	-0.8435***	0.1410***	-0.8397***	0.1405***	-0.8445***	0.1412***
	[-26.51]	[23.35]	[-27.04]	[23.72]	[-27.00]	[23.68]	[-27.23]	[23.79]	[-27.14]	[23.73]	[-27.25]	[23.80]
Age_25to44	-1.1405***	0.1547***	-1.1292***	0.1533***	-1.1290***	0.1532***	-1.1352***	0.1540***	-1.1287***	0.1532***	-1.1304***	0.1534***
	[-29.91]	[21.31]	[-29.56]	[21.07]	[-29.64]	[21.09]	[-30.05]	[21.30]	[-29.80]	[21.13]	[-29.87]	[21.18]
Age_45to64	-1.2923***	0.1705***	-1.2814***	0.1691***	-1.2943***	0.1708***	-1.2798***	0.1689***	-1.2727***	0.1679***	-1.2733***	0.1680***
	[-33.43]	[23.16]	[-33.31]	[23.09]	[-33.54]	[23.20]	[-33.59]	[23.16]	[-33.39]	[23.02]	[-33.40]	[23.03]
Age_65plus	-1.5343***	0.1929***	-1.5220***	0.1913***	-1.5291***	0.1922***	-1.5115***	0.1899***	-1.5042***	0.1890***	-1.5075***	0.1894***
	[-37.15]	[24.52]	[-37.09]	[24.49]	[-37.26]	[24.55]	[-37.22]	[24.43]	[-36.96]	[24.26]	[-37.07]	[24.34]

Table A5: **Effects of the Opioid Crisis on Credit Supply to Consumers: IV Regression Estimates (All Controls Shown) (continued)**

Panel B: Effects on Credit Card Terms: IV Second Stage (cont.)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables (continued):												
Married	0.1622***	-0.0262***	0.1577***	-0.0256***	0.1444***	-0.0238***	0.1630***	-0.0262***	0.1605***	-0.0259***	0.1588***	-0.0257***
	[8.00]	[-6.79]	[7.79]	[-6.65]	[7.05]	[-6.11]	[8.12]	[-6.83]	[8.00]	[-6.75]	[7.92]	[-6.69]
No_Kids	0.0247	0.0165***	0.0156	0.0177***	0.0167	0.0175***	0.0133	0.0180***	0.0142	0.0179***	0.0150	0.0178***
	[1.07]	[3.73]	[0.68]	[4.05]	[0.73]	[4.02]	[0.59]	[4.15]	[0.63]	[4.12]	[0.66]	[4.09]
White	-0.2598***	0.0303***	-0.2518***	0.0292***	-0.2535***	0.0295***	-0.2414***	0.0279***	-0.2391***	0.0276***	-0.2370***	0.0273***
	[-9.32]	[5.71]	[-9.20]	[5.61]	[-9.26]	[5.64]	[-9.04]	[5.45]	[-8.98]	[5.41]	[-8.91]	[5.36]
Miss_Race	0.0452	-0.0087	0.0941**	-0.0152**	0.0422	-0.0083	0.0659*	-0.0114	0.0696*	-0.0119*	0.0717*	-0.0122*
	[1.19]	[-1.21]	[2.50]	[-2.12]	[1.11]	[-1.15]	[1.79]	[-1.62]	[1.89]	[-1.69]	[1.95]	[-1.73]
Educ: Some_College	-0.0883***	0.0143***	-0.0952***	0.0152***	-0.0816***	0.0134***	-0.0676***	0.0115**	-0.0744***	0.0124**	-0.0687***	0.0117**
	[-3.32]	[2.82]	[-3.52]	[2.95]	[-3.12]	[2.68]	[-2.63]	[2.35]	[-2.89]	[2.52]	[-2.68]	[2.38]
Educ: College	-0.1201***	0.0397***	-0.1062***	0.0378***	-0.1040***	0.0376***	-0.0967***	0.0366***	-0.0937***	0.0362***	-0.0986***	0.0369***
	[-4.67]	[8.10]	[-4.22]	[7.90]	[-4.15]	[7.86]	[-3.89]	[7.69]	[-3.77]	[7.61]	[-3.97]	[7.75]
Educ: Post_College	-0.1762***	0.0551***	-0.1702***	0.0543***	-0.1758***	0.0550***	-0.1639***	0.0536***	-0.1678***	0.0541***	-0.1680***	0.0541***
	[-5.29]	[8.68]	[-5.12]	[8.58]	[-5.29]	[8.68]	[-4.98]	[8.51]	[-5.10]	[8.59]	[-5.10]	[8.59]
Miss Educ	-0.0993***	0.0371***	-0.1512***	0.0439***	-0.0953***	0.0366***	-0.1157***	0.0393***	-0.1156***	0.0393***	-0.1240***	0.0404***
	[-3.41]	[6.68]	[-4.99]	[7.61]	[-3.26]	[6.56]	[-4.05]	[7.19]	[-4.04]	[7.18]	[-4.32]	[7.35]
Homeowner	-0.1759***	0.0141***	-0.1729***	0.0137***	-0.1745***	0.0140***	-0.1914***	0.0162***	-0.1914***	0.0162***	-0.1837***	0.0152***
	[-9.57]	[4.04]	[-9.32]	[3.89]	[-9.49]	[3.98]	[-10.69]	[4.73]	[-10.69]	[4.73]	[-10.23]	[4.43]
Ln[Consumer Income]	-0.1218***	0.0330***	-0.1206***	0.0329***	-0.1142***	0.0320***	-0.1226***	0.0331***	-0.1220***	0.0330***	-0.1223***	0.0331***
	[-11.91]	[16.95]	[-11.74]	[16.80]	[-10.73]	[15.76]	[-12.14]	[17.12]	[-12.05]	[17.04]	[-12.09]	[17.08]
County Characteristics												
Ln[County Income]	-0.0007	0.0047*	-0.0071	0.0055**	-0.0066	0.0055**	0.0591***	-0.0031	0.0530***	-0.0023	0.0625***	-0.0035
	[-0.05]	[1.92]	[-0.51]	[2.09]	[-0.48]	[2.08]	[4.83]	[-1.32]	[4.65]	[-1.05]	[4.89]	[-1.44]
County Unemployment Rate	-0.0536***	0.0051**	-0.0299***	0.0020	-0.0391***	0.0032	-0.0223***	0.0010	-0.0254***	0.0014	-0.0210***	0.0008
	[-4.08]	[2.05]	[-3.32]	[1.17]	[-3.78]	[1.63]	[-2.73]	[0.63]	[-3.01]	[0.86]	[-2.59]	[0.52]
County Bank HHI	-0.2915***	0.0541***	-0.2542**	0.0492***	-0.1659*	0.0375**	0.0150	0.0142	0.0012	0.0160	0.0149	0.0143
	[-2.74]	[2.66]	[-2.54]	[2.58]	[-1.90]	[2.26]	[0.20]	[0.97]	[0.02]	[1.10]	[0.19]	[0.97]
County Population Density	0.0000***	-0.0000	0.0000***	-0.0000	0.0000***	-0.0000	0.0000**	0.0000**	0.0000**	0.0000**	0.0000*	0.0000**
	[4.12]	[-0.96]	[4.15]	[-1.15]	[4.11]	[-0.85]	[2.29]	[2.09]	[2.00]	[2.33]	[1.80]	[2.49]
County Race HHI	-0.1487***	0.0151	-0.1419**	0.0142	-0.1572***	0.0162	-0.1823***	0.0194*	-0.1499***	0.0152	-0.1970***	0.0214**
	[-2.60]	[1.38]	[-2.44]	[1.28]	[-2.81]	[1.52]	[-3.47]	[1.93]	[-2.65]	[1.40]	[-3.86]	[2.19]
County % Male	6.0714***	-0.8052***	3.1180***	-0.4156**	5.4814***	-0.7274***	4.3987***	-0.5614***	5.1985***	-0.6657***	4.3238***	-0.5516***
	[5.15]	[-3.59]	[3.15]	[-2.21]	[4.99]	[-3.47]	[4.37]	[-2.92]	[4.84]	[-3.24]	[4.32]	[-2.88]
County % Age_25_44	-2.6422***	0.2706*	-1.2609**	0.0883	-1.4771**	0.1169	-0.1523	-0.0578	-0.0435	-0.0720	-0.7702	0.0228
	[-3.23]	[1.74]	[-2.13]	[0.78]	[-2.39]	[0.99]	[-0.29]	[-0.58]	[-0.08]	[-0.72]	[-1.42]	[0.22]
County % Age_45_64	-1.2787*	0.3248**	-0.5348	0.2266**	-0.2799	0.1930**	0.0662	0.1441	-0.0496	0.1592*	-0.0786	0.1630*
	[-1.91]	[2.54]	[-0.97]	[2.17]	[-0.54]	[1.96]	[0.14]	[1.57]	[-0.10]	[1.70]	[-0.16]	[1.73]
County % Age_65plus	-0.8604	0.1357	-0.5124	0.0898	-1.0109	0.1555	0.4546	-0.0376	0.4258	-0.0338	0.1900	-0.0031
	[-1.38]	[1.14]	[-0.92]	[0.85]	[-1.55]	[1.25]	[1.12]	[-0.48]	[1.04]	[-0.43]	[0.44]	[-0.04]
County % High Education [$\geq$ College]	-0.7054***	0.0986***	-0.8793***	0.1216***	-0.6287***	0.0885***	-0.7262***	0.1015***	-0.6918***	0.0971***	-0.6144***	0.0870***
	[-5.46]	[4.00]	[-7.20]	[5.23]	[-4.60]	[3.39]	[-5.75]	[4.20]	[-5.36]	[3.93]	[-4.47]	[3.31]
County Inequality: Gini Coefficient	-0.7549*	0.1704**	-0.3048	0.1110*	0.2608	0.0364	0.0152	0.0687	0.2318	0.0404	-0.0542	0.0777
	[-1.92]	[2.27]	[-0.91]	[1.73]	[0.83]	[0.61]	[0.05]	[1.15]	[0.74]	[0.68]	[-0.17]	[1.29]
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender × Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.315	0.155	0.315	0.156	0.319	0.157	0.328	0.162	0.328	0.162	0.327	0.162

Table A7: **Effects of the Opioid Crisis on Credit Supply to Consumers: OLS Estimates**

This table reports consumer-level regression estimates from OLS regressions explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and bank credit card terms (rate spread and credit card limit) and credit card offer likelihood. Panel A reports results for credit card terms and Panel B reports results for credit card offer likelihood 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 offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Effects on Credit Card Terms

Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]	[9] Rate Spread	[10] Ln[Limit]	[11] Rate Spread	[12] Ln[Limit]
Independent Variables:												
Opioid Death Rate	0.0264***	-0.0046***										
	[3.90]	[-2.95]										
Top50th_Opioid Death Rate			0.0439***	-0.0124***								
			[4.13]	[-5.05]								
Top25th_Opioid Death Rate					0.0521***	-0.0146***						
					[4.27]	[-5.18]						
Opioid Prescription Rate							0.2058***	-0.0247***				
							[9.03]	[-4.69]				
Top50th_Opioid Prescription Rate									0.1204***	-0.0122***		
									[9.80]	[-4.31]		
Top25th_Opioid Prescription Rate											0.0750***	-0.0062*
											[5.40]	[-1.91]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	371,223	371,223	371,223	371,223	371,223	371,223	369,688	369,688	369,688	369,688	369,688	369,688
Adjusted R-squared	0.287	0.128	0.287	0.128	0.287	0.128	0.287	0.128	0.287	0.128	0.287	0.128

Panel B: Effects on Credit Card Offers

Dependent Variable:	[1] Card Offer	[2] Card Offer	[3] Card Offer	[4] Card Offer	[5] Card Offer	[6] Card Offer
Independent Variables:						
Opioid Death Rate	-0.0008***					
	[-9.44]					
Top50th_Opioid Death Rate		-0.0077***				
		[-6.62]				
Top25th_Opioid Death Rate			-0.0136***			
			[-10.14]			
Opioid Prescription Rate				-0.0094***		
				[-3.93]		
Top50th_Opioid Prescription Rate					-0.0041***	
					[-3.03]	
Top25th_Opioid Prescription Rate						0.0031**
						[2.03]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	752,275	752,275	752,275	749,396	749,396	749,396
Adjusted R-squared	0.169	0.169	0.169	0.169	0.169	0.169

Table A8: **Starting the Sample Earlier for the Credit Supply Analysis**

This table reports consumer-level IV 2SLS estimates for explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and bank credit card supply (rate spread, credit card limit, and credit card offers), when starting the sample earlier in 2007 (when the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File began being reported). The instrument is *High Purdue MKT '97-'02*, indicator for counties in upper 50th percentile of the percentage change in the quantity of OxyContin distributed by Purdue Pharma over 1997-2002. Panel A reports results for credit cards terms; Panel B reports results for credit card offer likelihood. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls for regressions include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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. Regressions include State x Year-Month fixed effects, and the credit card terms regressions also include Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Effects on Credit Card Terms

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5148**	-0.1169**					0.4737**	-0.1136**				
	[2.19]	[-2.18]					[2.13]	[-2.23]				
Top50th_Opioid Rate			1.3321**	-0.3026**					0.3685**	-0.0883**		
			[2.17]	[-2.15]					[2.13]	[-2.23]		
Top25th_Opioid Rate					1.9463**	-0.4421**					0.3633**	-0.0871**
					[2.15]	[-2.13]					[2.13]	[-2.23]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	487,606	487,606	487,606	487,606	487,606	487,606	485,246	485,246	485,246	485,246	485,246	485,246
Adjusted R-squared	0.195	0.093	0.174	0.070	0.158	0.051	0.202	0.101	0.201	0.100	0.201	0.100

Panel B: Effects on Credit Card Offers

	Opioid Death Rate			Opioid Prescription Rate		
	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]
Independent Variables:						
Opioid Rate	-0.0150***			-1.4427***		
	[-9.14]			[-7.50]		
Top50th_Opioid Rate		-0.2129***			-0.5065***	
		[-9.10]			[-8.91]	
Top25th_Opioid Rate			-0.5818***			-1.3438***
			[-8.45]			[-6.48]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	752,107	752,107	752,107	749,227	749,227	749,227
Adjusted R-squared	0.108	0.107	-0.039	-0.265	-0.017	-0.728

Table A9: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: IV Estimates for Prescription vs. Illicit Death Rates**

This table reports consumer-level regression estimates from IV 2SLS regressions explaining the relationship between opioid crisis intensity (measured as either prescription or illicit opioid deaths based on data from CDC) and bank credit card terms, rate spread, and credit card limit. Panel A reports the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument and Panel B reports second-stage IV estimates when using *High Purdue MKT '97-'02* as instrument. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: IV Estimates Using the *"MKT Doctors/1000Pop"* Instrument

	Prescription Opioid Deaths						Illicit Opioid Deaths					
Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]	[9] Rate Spread	[10] Ln[Limit]	[11] Rate Spread	[12] Rate Spread
Independent Variables:												
Opioid Death Rate	0.7732***	-0.1020***					1.2138***	-0.1601***				
	[3.89]	[-2.69]					[3.78]	[-2.65]				
Top50th_Opioid Death Rate			0.5404***	-0.0713***					1.7750***	-0.2342***		
			[3.89]	[-2.69]					[3.82]	[-2.67]		
Top25th_Opioid Death Rate					0.6393***	-0.0843***					1.3521***	-0.1784***
					[3.89]	[-2.69]					[3.86]	[-2.68]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,739	197,739	197,739	197,739	197,739	197,739
Adjusted R-squared	0.324	0.160	0.324	0.161	0.324	0.160	0.283	0.136	0.298	0.146	0.314	0.154

Panel B: IV Estimates Using the *"High Purdue MKT '97-'02"* Instrument

	Prescription Opioid Deaths						Illicit Opioid Deaths					
Dependent Variable:	[1] Rate Spread	[2] Ln[Limit]	[3] Rate Spread	[4] Ln[Limit]	[5] Rate Spread	[6] Ln[Limit]	[7] Rate Spread	[8] Ln[Limit]	[9] Rate Spread	[10] Ln[Limit]	[11] Rate Spread	[12] Rate Spread
Independent Variables:												
Opioid Death Rate	1.3996***	-0.2734**					1.1196***	-0.2187**				
	[2.63]	[-2.22]					[2.60]	[-2.21]				
Top50th_Opioid Death Rate			5.8772*	-1.1482*					4.3224**	-0.8445**		
			[1.95]	[-1.78]					[2.24]	[-1.98]		
Top25th_Opioid Death Rate					13.4732	-2.6323					2.6991**	-0.5273**
					[1.28]	[-1.22]					[2.51]	[-2.15]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	370,960	370,960	370,960	370,960	370,960	370,960	370,960	370,960	370,960	370,960	370,960	370,960
Adjusted R-squared	0.266	0.108	-0.325	-0.399	-2.095	-1.947	0.253	0.098	-0.009	-0.129	0.197	0.049

Table A10: **Additional Robustness Tests for the Credit Supply Analysis**

This table reports consumer-level IV 2SLS estimates using additional robustness tests for explaining the relationship between opioid crisis intensity (measured several ways based on data from CDC) and bank credit card terms, rate spread, and credit card limit. The instrument for opioid intensity is *MKT Doctors/1000Pop*, the number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. Panel A reports results when excluding the state of Florida, i.e., FL; Panel B excludes counties with zero opioid deaths in a particular year; Panel C uses opioid death measures using multiple causes of death rather than underlying death only; Panel D controls for even more county-level factors including labor participation rate, average credit score, air pollution index, house price index, percent of school dropouts, percent of religious population, politics (ratio of democratic to republican votes in each electoral year, poverty rate, percent of people with poor health, and crime rate; these additional variables are sourced from the U.S. Census American Community Surveys, the Social Explorer, the Federal Housing Finance Agency (FHFA), and the MIT Election Lab; Panel E-G excludes top & bottom 5% counties in terms of population density, income, and unemployment rate, respectively. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls for regressions include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Exclude "FL" State

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.9536***	-0.1272***					0.5634***	-0.0744***				
	[4.44]	[-3.13]					[4.58]	[-3.16]				
Top50th_Opioid Rate			1.8683***	-0.2493***					0.4208***	-0.0556***		
			[4.43]	[-3.13]					[4.58]	[-3.16]		
Top25th_Opioid Rate					1.6702***	-0.2229***					0.4849***	-0.0640***
					[4.48]	[-3.15]					[4.58]	[-3.15]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	183,246	183,246	183,246	183,246	183,246	183,246	183,242	183,242	183,242	183,242	183,242	183,242
Adjusted R-squared	0.293	0.142	0.292	0.143	0.306	0.150	0.329	0.165	0.329	0.164	0.329	0.164

Panel B: Exclude "Zero Deaths" Counties

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5239***	-0.0788***					0.3965***	-0.0595***				
	[3.39]	[-2.68]					[3.41]	[-2.76]				
Top50th_Opioid Rate			0.9799***	-0.1475***					0.2835***	-0.0425***		
			[3.39]	[-2.68]					[3.41]	[-2.76]		
Top25th_Opioid Rate					0.9468***	-0.1425***					0.3221***	-0.0483***
					[3.40]	[-2.68]					[3.41]	[-2.76]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	194,635	194,635	194,635	194,635	194,635	194,635	194,630	194,630	194,630	194,630	194,630	194,630
Adjusted R-squared	0.316	0.154	0.316	0.155	0.320	0.157	0.326	0.162	0.326	0.162	0.326	0.162

Table A10: **Additional Robustness Tests for the Credit Supply Analysis (continued)**

Panel C: Opioid Death Rates Using Multiple Death Causes

	Opioid Death Rate					
	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]
Independent Variables:						
Opioid Rate	0.5666***	-0.0748***				
	[3.87]	[-2.68]				
Top50th_Opioid Rate			1.1329***	-0.1495***		
			[3.86]	[-2.68]		
Top25th_Opioid Rate					1.0363***	-0.1367***
					[3.88]	[-2.68]
Consumer, County Controls	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739
Adjusted R-squared	0.316	0.155	0.314	0.155	0.320	0.157

Panel D: Control for Crime Rate & Other County Factors Together

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.9394***	-0.1913***					0.4483***	-0.0898***				
	[2.68]	[-2.92]					[2.81]	[-3.04]				
Top50th_Opioid Rate			1.7325***	-0.3528***					0.4456***	-0.0892***		
			[2.68]	[-2.92]					[2.81]	[-3.04]		
Top25th_Opioid Rate					1.2246***	-0.2494***					0.3556***	-0.0712***
					[2.72]	[-2.98]					[2.81]	[-3.04]
County Labor Participation Rate	-0.7466	-0.1775*	0.9246	-0.5179***	-0.2471	-0.2792***	0.2724	-0.3838***	0.2615	-0.3816***	0.4135	-0.4121***
	[-1.42]	[-1.75]	[1.45]	[-4.29]	[-0.52]	[-3.04]	[0.55]	[-4.04]	[0.53]	[-4.02]	[0.80]	[-4.19]
County Avg Credit Score	0.0069**	-0.0014**	0.0035	-0.0008*	0.0020	-0.0005	-0.0006	0.0001	0.0017	-0.0004	-0.0008	0.0001
	[2.00]	[-2.24]	[1.52]	[-1.75]	[1.10]	[-1.31]	[-0.45]	[0.30]	[1.00]	[-1.18]	[-0.65]	[0.52]
County Air Pollution	-0.0116*	0.0020*	-0.0430***	0.0084***	-0.0227***	0.0043***	-0.0125**	0.0022**	-0.0139**	0.0025**	-0.0082	0.0014
	[-1.90]	[1.77]	[-3.04]	[3.18]	[-2.89]	[2.92]	[-2.07]	[1.98]	[-2.24]	[2.17]	[-1.40]	[1.25]
County Δ HPI	-0.0237***	0.0053***	-0.0128**	0.0031***	0.0007	0.0003	0.0010	0.0003	0.0010	0.0003	0.0013	0.0002
	[-2.60]	[3.10]	[-2.32]	[2.94]	[0.23]	[0.50]	[0.32]	[0.44]	[0.30]	[0.46]	[0.39]	[0.36]
County % School Dropouts	-0.4206	-0.4180***	0.3223	-0.5693***	-1.2982**	-0.2393**	-2.1871***	-0.0600	-1.8962***	-0.1182	-2.2307***	-0.0512
	[-0.50]	[-2.65]	[0.30]	[-2.84]	[-2.13]	[-2.13]	[-4.40]	[-0.65]	[-3.69]	[-1.25]	[-4.50]	[-0.56]
County % Religious Pop	0.6086**	-0.0867	0.3774*	-0.0396	0.1678	0.0031	-0.2336**	0.0846***	-0.3248***	0.1029***	-0.2863***	0.0952***
	[2.02]	[-1.52]	[1.71]	[-0.94]	[1.10]	[0.11]	[-2.38]	[4.48]	[-2.90]	[4.83]	[-2.72]	[4.74]
County Politics	0.1436**	-0.0295**	0.1022**	-0.0210**	0.0268	-0.0057	0.0158	-0.0033	0.0380*	-0.0078*	0.0022	-0.0006
	[2.36]	[-2.57]	[2.23]	[-2.43]	[1.34]	[-1.48]	[0.96]	[-1.04]	[1.67]	[-1.80]	[0.16]	[-0.22]
County Poverty Rate	-3.0773	0.8813**	-0.0662	0.2681	-1.2238	0.5038**	1.1657*	0.0116	1.1079*	0.0232	1.0411	0.0366
	[-1.62]	[2.47]	[-0.07]	[1.52]	[-0.98]	[2.14]	[1.76]	[0.09]	[1.66]	[0.18]	[1.54]	[0.28]
County % Poor Health Pop	-0.0179**	0.0038**	-0.0191**	0.0041**	-0.0035	0.0009	-0.0008	0.0004	-0.0002	0.0002	-0.0009	0.0004
	[-2.12]	[2.34]	[-2.16]	[2.39]	[-0.73]	[0.92]	[-0.18]	[0.38]	[-0.05]	[0.25]	[-0.21]	[0.41]
County Crime Rate	-0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000
	[-0.38]	[1.50]	[0.69]	[0.54]	[1.29]	[0.00]	[1.03]	[0.26]	[0.57]	[0.69]	[1.58]	[-0.30]
Consumer, Other County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	165,975	165,975	165,975	165,975	165,975	165,975	165,983	165,983	165,983	165,983	165,983	165,983
Adjusted R-squared	0.300	0.121	0.296	0.117	0.316	0.144	0.327	0.160	0.327	0.159	0.327	0.160

Table A10: **Additional Robustness Tests for the Credit Supply Analysis (continued)**

Panel E: Exclude Top & Bottom 5% Counties in Terms of Population Density

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.7637***	-0.1162***					0.4945***	-0.0751***				
	[4.07]	[-3.25]					[4.18]	[-3.32]				
Top50th_Opioid Rate			1.2983***	-0.1975***					0.3620***	-0.0550***		
			[4.08]	[-3.26]					[4.18]	[-3.32]		
Top25th_Opioid Rate					1.4322***	-0.2179***					0.3841***	-0.0583***
					[4.08]	[-3.26]					[4.18]	[-3.32]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	181,517	181,517	181,517	181,517	181,517	181,517	181,534	181,534	181,534	181,534	181,534	181,534
Adjusted R-squared	0.308	0.146	0.310	0.149	0.311	0.149	0.328	0.162	0.327	0.162	0.327	0.162

Panel F: Exclude Top & Bottom 5% Counties in Terms of Income

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5594***	-0.0912***					0.3969***	-0.0645***				
	[3.31]	[-2.82]					[3.39]	[-2.87]				
Top50th_Opioid Rate			0.9293***	-0.1514***					0.2882***	-0.0468***		
			[3.32]	[-2.82]					[3.39]	[-2.87]		
Top25th_Opioid Rate					1.0632***	-0.1733***					0.3120***	-0.0507***
					[3.32]	[-2.82]					[3.39]	[-2.87]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	182,085	182,085	182,085	182,085	182,085	182,085	182,102	182,102	182,102	182,102	182,102	182,102
Adjusted R-squared	0.318	0.150	0.321	0.154	0.321	0.153	0.330	0.161	0.330	0.161	0.329	0.161

Panel G: Exclude Top & Bottom 5% Counties in Terms of Unemployment Rate

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5928***	-0.0967***					0.4348***	-0.0703***				
	[3.68]	[-3.13]					[3.72]	[-3.14]				
Top50th_Opioid Rate			1.0540***	-0.1718***					0.3207***	-0.0518***		
			[3.68]	[-3.14]					[3.72]	[-3.14]		
Top25th_Opioid Rate					1.0029***	-0.1635***					0.3442***	-0.0556***
					[3.69]	[-3.14]					[3.72]	[-3.14]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	179,019	179,019	179,019	179,019	179,019	179,019	179,017	179,017	179,017	179,017	179,017	179,017
Adjusted R-squared	0.316	0.150	0.316	0.152	0.320	0.155	0.328	0.162	0.328	0.162	0.328	0.162

Table A11: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects by Additional Risk and Demographics using IV Methodology**

This table examines how the effects of opioid crisis intensity on bank credit card terms (rate spread and credit card limit) differ by additional consumer characteristics (using interactions of the characteristic and opioid intensity): past bankruptcy filings or not in Panel A; low-income (consumer income < 30K) in Panel B; working age (age between 25 and 64 years old) or not in Panel C; low education (< college) or not in Panel D. All results report the second-stage IV estimates when using *MKT Doctors/1000Pop* as instrument for opioid intensity, the number of doctors in the county who received marketing payments from pharmaceutical companies to prescribe opioids per 1,000 county population each year. All variables are constructed using the anonymized Mintel Comperemedia Inc. Direct Mail Monitor Data and TransUnion LLC Match File for analyzing credit card offers. The data are focused on lenders identified as banks in the Mintel/TransUnion Match File, and credit score and score ranges are based on the VantageScore 3.0. Demographic attributes are from Mintel. Consumer and loan controls include credit score ranges, indicators for past deep delinquency, recent delinquency, past derogatory filings such as foreclosure, collections etc., 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, and Lender x Year-Month fixed effects. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Consumer Risk: Bankruptcy Filing or Not

	Opioid Death Rate						Opioid Prescription Rate					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Ln(Limit)	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.8650***	-0.0859***					0.3373***	-0.0618***				
	(4.83)	(-2.86)					(2.98)	(-2.85)				
Opioid Rate × Bankruptcy_Filer	4.9700***	-0.0490					1.8816***	-0.0037				
	(8.71)	(-0.51)					(9.50)	(-0.10)				
Top50th_Opioid Rate			1.6811***	-0.1625***					0.2399***	-0.0453***		
			(5.17)	(-2.86)					(2.88)	(-2.84)		
Top50th_Opioid Rate × Bankruptcy_Filer			8.6720***	-0.0760					1.5350***	-0.0005		
			(9.03)	(-0.45)					(9.36)	(-0.02)		
Top25th_Opioid Rate					0.8679***	-0.1491***					0.2269**	-0.0495***
					(3.09)	(-2.87)					(2.47)	(-2.82)
Top25th_Opioid Rate × Bankruptcy_Filer					6.3494***	-0.0538					1.7968***	-0.0018
					(9.57)	(-0.44)					(9.40)	(-0.05)
Bankruptcy_Filer	-6.3877***	0.1084	-4.3874***	0.0808	-1.6994***	0.0604	-1.1538***	0.0399	-0.6416***	0.0384*	-0.2966***	0.0381***
	(-8.37)	(0.85)	(-8.50)	(0.90)	(-8.25)	(1.59)	(-7.48)	(1.35)	(-6.24)	(1.95)	(-4.27)	(2.87)
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.111	0.151	0.183	0.153	0.274	0.156	0.327	0.162	0.325	0.162	0.324	0.162

Panel B: Consumer Risk: Low Income or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.5183***	-0.0763**					0.3238***	-0.0502**				
	[3.28]	[-2.53]					[2.75]	[-2.23]				
Opioid Rate × Low Income [<30K]	0.4328***	-0.0340					0.4978***	-0.0451				
	[2.62]	[-1.08]					[3.41]	[-1.61]				
Top50th_Opioid Rate			0.9458***	-0.1390**					0.2289***	-0.0359**		
			[3.29]	[-2.54]					[2.66]	[-2.18]		
Top50th_Opioid Rate × Low Income [<30K]			1.3483***	-0.1254*					0.5094***	-0.0480*		
			[3.49]	[-1.71]					[3.68]	[-1.81]		
Top25th_Opioid Rate					0.9130***	-0.1363**					0.2299**	-0.0376**
					[3.14]	[-2.46]					[2.35]	[-2.01]
Top25th_Opioid Rate × Low Income [¡30K]					1.0797***	-0.0898					0.5080***	-0.0463
					[2.87]	[-1.26]					[3.45]	[-1.64]
Low Income [<30K]	-0.2789	0.0087	-0.4546**	0.0328	-0.0792	-0.0037	-0.1416	0.0034	-0.0486	-0.0041	0.0791	-0.0165
	[-1.36]	[0.22]	[-2.21]	[0.84]	[-0.73]	[-0.18]	[-1.22]	[0.15]	[-0.58]	[-0.25]	[1.50]	[-1.63]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.312	0.152	0.307	0.151	0.315	0.154	0.327	0.161	0.327	0.161	0.327	0.161

Table A11: **Effects of the Opioid Crisis on Credit Card Supply to Consumers: Heterogeneous Effects by Additional Risk and Demographics using IV Methodology (continued)**

Panel C: Working Age 25-64 or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	1.1547***	-0.0902**					0.9302***	-0.0718**				
	[5.91]	[-2.44]					[6.00]	[-2.43]				
Opioid Rate × Age_25_64	-0.5789***	0.0058					-0.5947***	0.0113				
	[-3.90]	[0.21]					[-4.31]	[0.43]				
Top50th_Opioid Rate			2.1341***	-0.1670**					0.6965***	-0.0512**		
			[5.92]	[-2.45]					[6.01]	[-2.32]		
Top50th_Opioid Rate × Age_25_64			-1.1224***	0.0086					-0.4574***	0.0057		
			[-3.83]	[0.15]					[-4.07]	[0.27]		
Top25th_Opioid Rate					2.1240***	-0.1613**					0.9020***	-0.0631**
					[5.95]	[-2.38]					[5.99]	[-2.19]
Top25th_Opioid Rate × Age_25_64					-1.1652***	0.0064					-0.6665***	0.0156
					[-3.78]	[0.11]					[-4.48]	[0.55]
Age_25_64	0.6532***	0.0097	0.5223***	0.0125	0.2438***	0.0155	0.3587***	0.0100	0.1644***	0.0152	0.1061**	0.0136*
	[3.56]	[0.28]	[3.41]	[0.43]	[2.94]	[0.98]	[3.54]	[0.52]	[2.72]	[1.32]	[2.50]	[1.68]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.299	0.150	0.302	0.151	0.308	0.153	0.322	0.160	0.322	0.160	0.321	0.160

Panel D: Low Education or Not

	Opioid Death Rate						Opioid Prescription Rate					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Dependent Variable:	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Ln[Limit]	Rate Spread	Rate Spread
Independent Variables:												
Opioid Rate	0.6217***	-0.0724**					0.4555***	-0.0521**				
	[3.88]	[-2.38]					[3.94]	[-2.36]				
Opioid Rate × Low_Educ[< College]	-0.0934	-0.0113					-0.0907	-0.0315				
	[-0.90]	[-0.57]					[-0.48]	[-0.86]				
Top50th_Opioid Rate			1.2275***	-0.1384**					0.3336***	-0.0389**		
			[3.85]	[-2.28]					[3.96]	[-2.41]		
Top50th_Opioid Rate × Low_Educ[<College]			-0.3543	-0.0175					-0.0411	-0.0272		
			[-1.24]	[-0.32]					[-0.29]	[-0.99]		
Top25th_Opioid Rate					1.1723***	-0.1320**					0.3701***	-0.0416**
					[3.86]	[-2.28]					[3.92]	[-2.31]
Top25th_Opioid Rate × Low_Educ[<College]					-0.3177	-0.0277					-0.0830	-0.0275
					[-1.04]	[-0.48]					[-0.49]	[-0.85]
Low_Educ[<College]	0.2321*	-0.0225	0.3055**	-0.0259	0.1983**	-0.0263	0.1695	-0.0088	0.1252	-0.0186	0.1255**	-0.0259***
	[1.85]	[-0.94]	[1.97]	[-0.88]	[2.21]	[-1.54]	[1.14]	[-0.31]	[1.54]	[-1.19]	[2.44]	[-2.63]
Consumer, County Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
State, Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Lender x Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197,739	197,739	197,739	197,739	197,739	197,739	197,735	197,735	197,735	197,735	197,735	197,735
Adjusted R-squared	0.314	0.155	0.313	0.156	0.318	0.157	0.328	0.162	0.328	0.162	0.327	0.162

Table A12: **Effects of Opioid-Related Laws on Opioid Prescriptions and Deaths Rates**

This table uses county-level data and conducts a horse race among several opioid-related state laws examining their effects on opioid prescription and deaths rates (using difference-in-difference regressions in which we interact the individual state laws with post-adoption indicators for each law and state), a horse race among four different state opioid-related laws (Opioid Limiting Law, PDMP Law, Naloxone Law, and Good Samaritan Law) as well as state indicators for Triplicate Prescription Law and Medical Marijuana Permitting Law, the latter two being time-invariant over our sample period. 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. Regressions include County, State, and Year fixed effects in columns 1-4 and Year fixed effects in columns 5-8. Heteroskedasticity-robust t-statistics are reported in parentheses below coefficient estimates. Variable definitions and data sources are in Appendix Table A1. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Dependent Variable:	[1] Opioid Prescription Rate	[2] Opioid Deaths Rate	[3] Opioid Prescription Deaths Rate	[4] Opioid Illicit Deaths Rate	[5] Opioid Prescription Rate	[6] Opioid Deaths Rate	[7] Opioid Prescription Deaths Rate	[8] Opioid Illicit Deaths Rate
Independent Variables:								
Post × State Prescription Limiting Law	-0.0297***	0.2317***	-0.0400***	0.2941***				
	[-5.10]	[10.78]	[-2.84]	[16.39]				
Post × State PDMP Law	-0.0757***	0.1754***	-0.0785***	0.3011***				
	[-17.04]	[7.73]	[-4.54]	[18.49]				
Post × State Naloxone Law	0.001	0.017	0.0213	[0.007]				
	[0.27]	[0.95]	[1.59]	[-0.56]				
Post × State Good Samaritan Law	-0.0128***	0.0360**	0.0026	0.0334***				
	[-3.64]	[2.12]	[0.21]	[2.66]				
State Triplicate Prescription Law					-0.1215***	-0.3287***	-0.2054***	-0.1699***
					[-19.85]	[-25.37]	[-23.46]	[-17.62]
Medical Marijuana Permitting Law					-0.0701***	0.0554***	-0.0450***	0.1106***
					[-13.81]	[4.23]	[-5.21]	[11.16]
County Controls	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	NO	NO	NO	NO
State FE	YES	YES	YES	YES	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	27,955	30,563	30,563	30,563	28,052	30,565	30,565	30,565
Adjusted R-squared	0.866	0.488	0.394	0.474	0.295	0.136	0.063	0.193