The Opioid Epidemic and Consumer Credit Supply: Evidence from Credit Cards

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Introduction

- Longest deadly ongoing national health crisis in the U.S. Stats Over Time By Demos
- Growing evidence opioid abuse ↓ labor force participation and ↑ unemployment.
  - Opioids affect worker health and reduce longevity. (e.g., Case and Deaton, 2015).
  - Drug misusers more likely absent from work. (e.g., Van Hasselt, Keyes, Bray and Miller, 2015).
  - Depressed labor force participation intertwined the opioid crisis (e.g., Krueger, 2017).
  - Strong ↓ on employment-to-population, hours worked, earnings; ↑ in unemployment and disability applications and beneficiaries (e.g., Case and Deaton, 2015; Park and Powell, 2020).
  - Strong negative labor effects on both prime age men and women (e.g., Case and Deaton, 2015).
  - Opioids ↓ subsequent individual employment (e.g., Ouimet, Simintzi and Ye, 2020).
- Crisis affects consumers and communities financial health and poses evolving and elusive risks to lenders supplying credit to consumers due to information asymmetry.
  - Evidence on municipal bond issuance, subprime auto performance, house values, bank deposits (Cornaggia, Hund, Nguyen and Ye, 2021; Custodio, Cvijanovic and Wiedeman, 2021; Jansen, 2021; Li and Ye, 2022)).

Big picture on this paper and what we find

- Contribution: Add to the literature by examining the spillover effects of the opioid crisis on consumer credit supply and the effectiveness of recent anti-opioid laws/regulations.
  - Use the consumer credit card market as a laboratory.
  - To disentangle credit supply, use unsolicited credit card offer mailings by banks to consumers
  - To identify causal effects, we employ instrumental variables, PSM, and contiguous counties, and a battery of supply and demand factors and fixed effects.

- Main Results:
  - We find that banks $\downarrow$ credit supply to consumers significantly in counties highly exposed to opioid abuse by offering higher interest rates, lower credit card limits, less rewards, and reduce overall credit offers.
    - The adverse effects are stronger for riskier consumers, minorities, younger people, and people with lower income.
  - Supply-oriented laws are somewhat helpful, but demand-oriented laws are not.
  - Opioid-induced credit supply contraction led to $\downarrow$ in local consumer spending, suggesting important social welfare implications.

Literature

- Large literature on the origins of the opioid crisis.
  - See Currie and Schwandt (2021) and Maclean, Mallatt, Ruhm and Simon (2020) for a review.
  - Neither contemporaneous nor long-term economic conditions can explain the epidemic.
  - Instead, physicians' beliefs in pain medication, aggressive marketing by pharmaceutical companies, little past public oversight are the key driving forces.
- Literature on the economic impact of the opioid crisis.
  - Labor market (discussed above)
  - Firm formation, survival and growth (e.g., Ouimet, Simintzi and Ye (2020), Rietveld and Patel (2021), Sumell (2020), Langford (2021)).
- Small but growing literature on the effects of the opioid crisis on finance.
  - Municipal bond, local house value, subprime auto loan performance, bank deposits

Theoretical Arguments

- Individuals residing in areas with higher opioid exposure may be more at-risk for opioid abuse or addiction and hence financially vulnerable.
  - For highly dependent substance abusers, cost of drugs alone can throw off finances, they are also less employable.
  - The addiction can further lead to other unsound financial decisions due to a "reinforcer pathology" (e.g., Bickel, Athamneh, Snider, Craft, DeHart, Kaplan and Basso (2020)).

- Lenders may curtail credit supply via harsher terms and less credit offered if they try to reduce credit risk exposure from opioid abuse if consumers default more in highly affected areas, which pushes upward their loan portfolio risk.
  - Banks care about long-term viable consumers, opioid-affected not viable in long term.
  - Banks may also incur increased costs for screening and ongoing monitoring.
  - Given difficulty to separate long-term viable from nonviable customers due to information asymmetry and social stigma, banks reduce credit in the affected markets along both the intensive margin (higher spread, lower limit) and the extensive margin (reduced offer, (Stiglitz and Weiss 1981)).

Data and Empirical Challenges

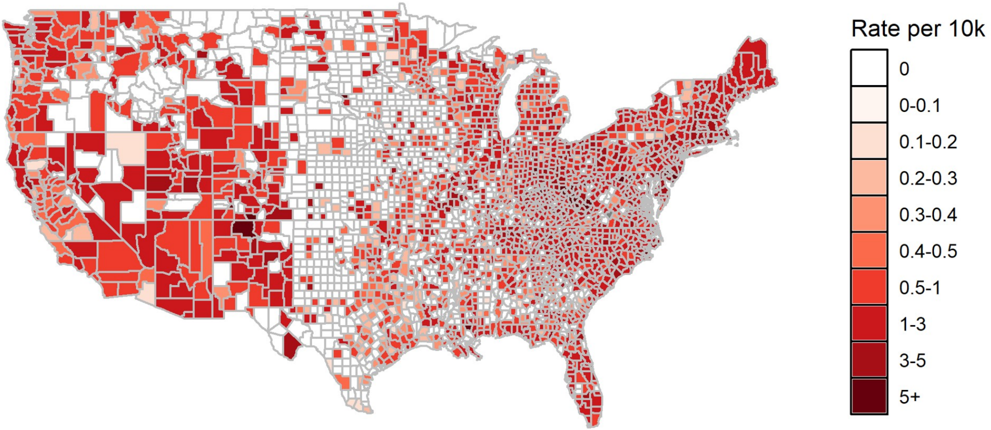
Our Approach: Data

- Opioid Mortality Rates: (Confidential) CDC All-County Mortality Micro Data.
- Credit Supply: unsolicited credit card offer mailings by banks to consumers from the Anonymized Mintel Direct Mail Monitor Data & TransUnion LLC Match File.
  - Proprietary survey of nationally representative US consumers merged with TransUnion credit bureau consumer data. Credit offers are a direct informative measure of consumer credit supply, helping circumvent challenges of disentangling supply from demand forces that plague other studies (e.g., Han, Keys and Li (2018)).
- Supplemental Data:
  - Opioid Marketing: Centers for Medicare and Medicaid Services Open Payment database.
  - Consumer Credit Performance and Local Consumption: FR Y-14M supervisory regulatory credit card data reported to the Federal Reserve System by large U.S. BHCs for stress testing purposes.
  - Bank-level Consumer Portfolio Data: Call Report.
  - Other County-level Economic Data: BLS, Census ACS, FDIC SOD, and other sources.

Measurement of Opioid Abuse

- Do not observe individual opioid usage nor health status. We follow the literature and construct county level opioid crisis exposure measures based on opioid death rates
  - Based on confidential opioid-related death rates collected from the CDC/National Vital Statistics System (NCHS).
  - The measures serve as proxies for the opioid epidemic severity and help tackle the challenge of not observing consumers' opioid use or abuse or their general health.
  - Consumers' drug abuse is then measured via the severity of the opioid crisis based on opioid deaths in the consumer's county of residence.
  - This measurement likely replicates the financial institutions' credit risk management models.
    - That is, in the absence of perfect information on the affected individuals, financial institutions' credit models resort to instead capturing average opioid risk treatment based on the crisis intensity in the individuals' local market of residence.
  - We then ask: Are banks less likely to supply credit or apply more stringent terms to individuals living in more opioid-affected areas?

Opioid Death Rates across US Counties (2019)



Empirical Challenges: Endogeneity

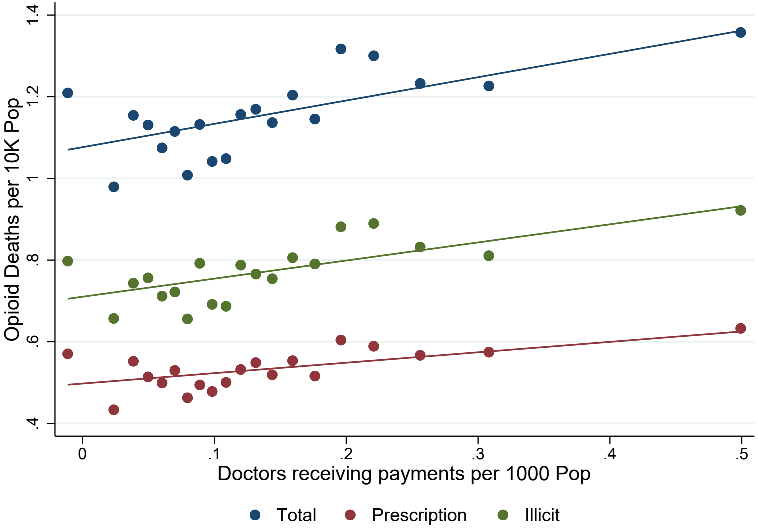
- Common conditions/shocks drive both the opioid crisis intensity and credit outcomes.
  - Conduct two-stage least square (2SLS) regression analyses that use instrumental variables for the opioid crisis intensity.
  - Introduce extensive sets of control variables and fixed effects that capture heterogeneity in county, consumer, and bank characteristics as relevant in different parts of our analyses.

- Other confounding consumer events or crises could affect our results.
  - Focus on the years 2010-2019 so that our results are not contaminated by the implementation of the Credit CARD Act of 2009, the Global Financial Crisis over 2007-2009, or the COVID-19 outbreak from 2020 onwards.
    - These ten years 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.
  - Focus on opioid death rates as the primary measure of crisis intensity and use prescriptions as robustness. In addition to being comprehensive and comparable across counties, it may better capture the development in the opioid epidemic since 2010, the period of our analyses, that is, the rise in illicit opioid drug use.

Instrument: "MKT Doctors/1000Pop"

- MKT Doctors/1000Pop, captures the scale of pharmaceutical industry's opioid marketing to physicians, particularly the number of physicians that receive non-research marketing visits and payments related to opioids per 1000 population in a county.
  - Follows Hadland, Rivera-Aguirre, Marshall and Cerda (2019).
- The data for this instrument was acquired as part of disclosure requirements mandated by the Physician Payments Sunshine Act and is collected from Centers for Medicare and Medicaid Services Open Payments database.
  - Hadland, Krieger and Marshall (2017) show that pharmaceutical companies invest tens of millions of dollars annually in direct-to-physician marketing of opioids.
  - 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 to be correlated with consumer or bank credit behavior other than through the increased risks imposed by the opioid abuse itself.

Validating Instrument: Relevancy



Validating Instrument: More Checks

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

- Several studies have shown 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. (Aliprantis, Lee and Schweitzer (2020); Currie and Schwandt (2021); Alpert, Evans, Lieber, Powell (2022)).
- Table shows little correlation between the instrument and various economic and other county characteristics.

Methodology

IV Empirical Models: First Stage

- In the IV 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:

$$OpioidExp_{c,t-1} =$$
$$\beta_0 + \beta_1 IV_{c,t-1} + \beta_2 CountyControls_{c,t-1} + +\beta_3 OtherConsumer/BankControls_{i,c,t-1} + OtherFE + \epsilon_{i,t}$$

- where:
  - where i indexes individual or bank, c indexes county, and t indexes time periods (months or quarters).
  - OpioidExp = the opioid crisis exposure variable, opioid death rates or opioid prescription rates measured either continuously or as a dummy indicating whether the county is in the nation's top 50 percentile.
  - IV= The main instrumental variable is 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 onwards.

IV Empirical Models: Second Stage for Consumer Credit Supply

- In IV second stage, we examine the relation between predicted opioid crisis exposure and consumer credit supply using the equation:

$$Y_{i,c,t} = \gamma_0 + \gamma_1 \widehat{OpioidExp}_{c,t-1} + +\gamma_3 ConsumerControls_{i,t-1} + {}_4 CountyControls_{c,t-1} + FE + \mu_{i,c,t}$$

- where:
  - i indexes consumer, c indexes county, and t indexes time periods (months).
  - $Y_{i,c,t}$ = credit card offer terms such as the *RateSpread,* difference between the offered credit card APR and one-month Treasury-bill, or *Ln(Limit),* the natural log of the offered credit card limit.
  - $\text{ConsumerControls}_{i,t-1}$= consumer controls (as of 2-3 months prior to offer): credit score, consumer income, recent and past delinquency (90+ days), other derogatory information such as foreclosures, past bankruptcy filings, previous other credit cards, previous high credit utilization (80% or higher), natural log of the number of recent credit inquiries (proxying for credit demand), age, homeowner, married, no children, education level, and indicator for non-minority/white consumers.
  - $\text{CountyControls}_{c,t-1}$ = 11 county controls (lagged one period): median income, unemployment rate, bank local market concentration, population density, percent of male, race concentration, percent of people in various age ranges, percent high education, and inequality (gini coefficient).
  - FEs: state by year-month, lender by year-month, lender by state, lender, state, year-month.
  - Errors are double-clustered by marketing campaign and year-month.

Empirical Results

Main Results: Opioid Epidemic and Consumer Credit Supply — IV First Stage

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

Main Results: Opioid Epidemic and Consumer Credit Supply — IV Second Stage

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

Prescribed vs. Illicit Opioid Deaths — IV Second Stage

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

Alternative Exposure Measure: Prescription Rates — IV Second Stage

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

Alternative IV: MKTPayments/1000Pop — IV Second Stage

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

Alternative IV: High Purdue MKT — IV Second Stage

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

Heterogenous Effects: High Credit Risk Consumers (Score < 620) — IV Second Stage

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

Heterogenous Effects: Minority Consumers — IV Second Stage

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

Extensive Margin: Rewards/Promotions — IV Second Stage

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

Extensive Margin: Likelihood of Credit Card Offer — IV Second Stage

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

Understanding the Mechanisms: Y-14M Consumer Behavior/Quality — IV Second Stage

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

Understanding the Mechanisms: Call Reports Bank Card Portfolio Quality — IV Second Stage

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

Reconfirming main effects with different dataset: Y-14M Card Terms — IV Second Stage

Dependent Variables:	Avg Cycle APR	Ln(Avg Limit)	Pct Cards w/ Rewards	Avg Cycle APR	Ln(Avg Limit)	Pct Cards w/ Rewards
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$	0.3433***	-0.0158*	-0.0178***			
	(5.30)	(-1.89)	(-4.12)			
High Opioid Death Rate$_{c,t-1}$				2.1138***	-0.0973*	-0.1099***
				(5.17)	(-1.88)	(-4.06)
Fit statistics						
Observations	1,008,285	1,009,322	1,009,322	1,008,285	1,009,322	1,009,322
Adj. R^2	0.001	0.055	0.002	0.001	0.048	0.001
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓

Opioid Abuse and Local Consumption — IV Second Stage

Dependent Variables:	Total Purchase /Pop	Total Purchase /Limit	Ln (Avg Purchase)	Total Purchase /Pop	Total Purchase /Limit	Ln (Avg Purchase)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Opioid Death Rate$_{c,t-1}$	-0.0070***	-0.0149***	-0.0920**			
	(-6.90)	(-6.14)	(-2.40)			
High Opioid Death Rate$_{c,t-1}$				-0.0431***	-0.0922***	-0.5705**
				(-6.65)	(-5.95)	(-2.39)
Fit statistics						
Observations	1,008,631	1,008,631	1,004,460	1,008,631	1,008,631	1,004,460
Adj. R^2	0.021	0.001	0.151	0.010	0.001	0.142
Fixed effects						
State × Year-Month	✓	✓	✓	✓	✓	✓
Lender × Year-Month	✓	✓	✓	✓	✓	✓
Lender × State	✓	✓	✓	✓	✓	✓
Lender, State, Year-Month	✓	✓	✓	✓	✓	✓
County controls	✓	✓	✓	✓	✓	✓

Opioid Supply-Oriented Laws

Name	Description	Implementing States & First Year Implemented	Source
Supply-Related Laws			
"Opioid Limiting Law"	Limits 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.	2016: AZ, CT, ME, MA, NE, NH, NY, NC, PA, RI; 2017: AK, CO, DE, HI, ID, KY, LA, MI, MN, MO, NV, NJ, OH, UT, VT, VA, WA; 2018: FL, OK, SC, TN, WV.	The Ballotpedia, Opioid Prescription Polcies by States, the National Conference of State Legislators (NCSL), Individual State Websites & Custodio, Cvijanovic and Wiedemann (2021)
Mandatory "Opioid PDMP Law"	The Prescription Drug Monitoring Program (PDMP) collects and tracks opioid prescriptions and connect prescribers, dispensers, law enforcement, and Medicare authorities. The mandatory law requires that prescribers must access the PDMP system before prescribing an opioid as interpreted by the Prescription Drug Abuse Policy System (PDAPS).	2012: KY, NM, WV; 2013: NY, TN, VT; 2014: GA, IN, MA; 2015: CT, NJ, NV, OH, OK, VA; 2016: NH, RI.	The Opioid Environment Policy Scan (OEPS), University of Chicago
"Triplicate Prescription Law"	Requires three copies of an opioid prescription issued and kept by, respectively, the prescriber, the pharmacist, and a state agency that maintains a database from these forms to monitor and investigate prescribing irregularities and diversion.	States with active triplicate programs at the time of OxyContin's launch in 1996: CA, ID, IL, NY, and TX.	Alpert, Evans, Lieber and Powell (2022)

Opioid Demand/User-Oriented Laws

Name	Description	Implementing States & First Year Implemented	Source
Demand-Related Laws			
"Naloxone Law"	Increases access to and allows 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.	Passed law before 2010: CA, CT, NM, NY; in 2010: IL, WA; 2012: MA, RI; 2013: CO, DC, KY, MD, NJ, NC, OK, OR, VT, VA; 2014: DE, GA, ME, MI, MN, OH, PA, TN, UT, WI; 2015: AL, AR, FL, ID, IN, LA, MS, NE, NV, NH, ND, SC, TX, WV; 2016: AK, AZ, HI, IA, MO, SD; 2017: KS, MT, WY.	The Opioid Environment Policy Scan (OEPS), University of Chicago
"Good Samaritan Law"	Provides immunity to drug users for certain drug crimes when they call for help for a person experiencing a drug overdose, again potentially helping reduce deaths.	Any Samaritan Law started before 2010: AK, KS, ME, MD, NM, OK, TX, WY; in 2010: WA; 2011: CT; NY; 2012: CO, FL, IL, MA, RI; 2013: CA, DE, DC, NJ, NC, VT; 2014: GA, IN, LA, MN, PA, UT, WI; 2015: AL, AR, HI, KY, MS, NV, NH, ND, TN, VA, WV; 2016: OH, OR; 2017: MI, MO, MT, NE, SC, SD; 2018: AZ, ID, IA.	The Opioid Environment Policy Scan (OEPS), University of Chicago
"Medical Marijuana Permitting Law"	Accepts and legalizes marijuana for medical purposes.	Law in effect during our sample period (2010-2019): AK, AZ, AR, CA, CO, CT, DE, DC, FL, HI, IL, ME, MD, MA, MI, MN, MT, NV, NH, NJ, NM, NY, OH, OR, PA, RI, VT, WA.	The Opioid Environment Policy Scan (OEPS), University of Chicago

Opioid State-Level Supply and Demand Laws — IV Second Stage

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

Opioid State-Level Supply and Demand Laws (cont.) — IV Second Stage

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

Opioid State-Level Supply and Demand Laws (cont.) — IV Second Stage

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

Opioid State-Level Supply and Demand Laws (cont.) — IV Second Stage

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

Additional Identification and Other Robustness Checks

- Conduct tests to address identification and/or rule out alternative explanations:
  - Employ PSM analyses where we match the high-quartile opioid deaths counties to other non-treated counties by year and county characteristics using several matching techniques.
  - Use contiguous counties to high opioid death counties only
  - Control for nine more local market factors.
  - Use multiple death causes instead of underlying causes.
  - Exclude Florida, which was an epicenter for the opioid crisis distribution.
  - Exclude zero-death counties.
  - Reconfirm main results also using FR Y14-M credit card supervisory data.
  - Conduct additional cross-sectional tests by consumer characteristics.

- All of our approaches consistently show statistically as well as economically significant adverse effects on consumer credit risk and credit supply caused by opioid abuse.
  - Additionally, although the crisis affected the overall population, the negative effects are larger for riskier, minorities (particularly Blacks), low income, and younger consumers.

Key Takeaways

- This paper investigates the effects of the opioid crisis on consumer credit markets.
- We have several key findings, all economically sizable:
  - Credit supply to consumers: Banks have become reluctant to lend in areas with significant exposure to opioids: i) they are less likely to send their offers of credit in the exposed regions; ii) when they do solicit consumers for credit in those areas, the offers have $\uparrow$ higher interest rates and $\downarrow$ lower credit limits.
  - Local consumer consumption: local consumer spending significantly $\downarrow$ in the highly opioid-crisis affected areas.
- The current wave of laws and regulations passed to reduce the devastating effects of the opioid crisis on communities $\rightarrow$ mixed effects.
  - The supply-oriented laws (Opioid Prescription Limiting Law, the mandatory PDMPs, and the Triplicate Prescription Law) appear to help mitigate some of the negative influence of the opioid epidemic, including both on some of opioid deaths as well as revert some of the negative effects on consumer credit supply.
  - The demand-oriented laws are less beneficial as per findings in our analysis.

Policy Implications

- From a policy standpoint, the cautious behavior of banks appears to be partially justified by the relatively higher credit risk in the highly opioid-affected areas.
  - The $\downarrow$ consumer credit supply, nevertheless, could create a negative feedback loop depriving the opioid-affected regions of the much-needed liquidity for recovery.
  - The $\downarrow$ consumer consumption in hardly-hit local markets may suggest important negative externalities $\rightarrow$ social welfare and macro-policy implications — given that consumer spending accounts for the vast majority of US gross domestic product and economic growth.

- These findings here may prove useful for policymakers to better understand the impact of the opioid crisis and formulate adequate policies concerning consumers to help recovery efforts, enhance welfare, and restore growth and resilience in the opioid-affected consumer markets.

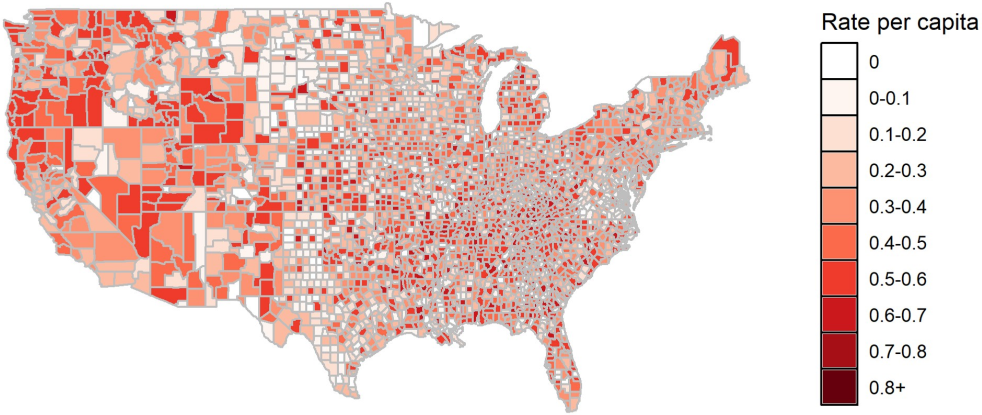
Thank you!

Big picture on the Opioid Epidemic

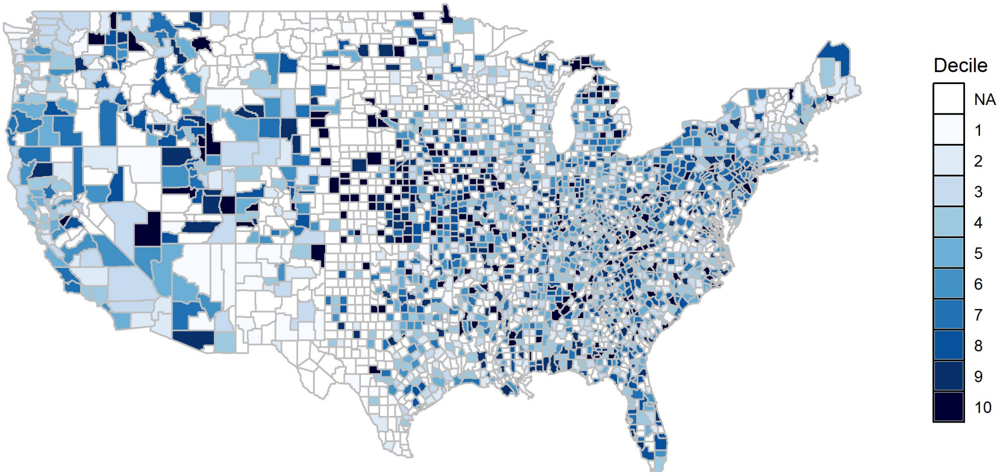
- The opioid epidemic has led to a staggering number of overdose deaths, opioid disorders, family breakups, and community problems.
  - $>$ 1 million American people died from 1999 to present.
  - $>$ 2 millions Americans are struggling with opioid disorders.
  - More and more deadly over time, affecting a larger spectra of the population.
  - $>$ 30% of patients prescribed opioids for chronic pain end up misusing them.
  - Rise of fentanyl critical concern: involved in over half of opioid-related overdose deaths.
- Behind every statistic is a real person, a real family, and a real community suffering. This epidemic is not just a number; it's a human tragedy that demands attention and action.
  - "Addiction is a family disease; one person uses, but whole family suffers." - Sherry Woodard
  - "This epidemic doesn't discriminate; it affects people of all backgrounds." - Chris Christie
  - "Addiction is a health issue, not a moral failing." - Michael Botticelli
  - "The opioid epidemic is a national emergency." - Alex Azar, Donald Trump
  - "This is a battle we cannot afford to lose." - Joe Biden

Return

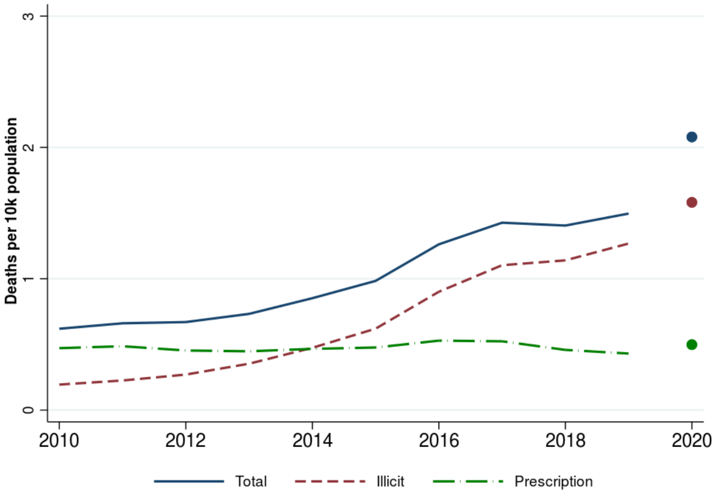
Additional Figures: Prescription Rates across US Counties (2019)



Additional Figures: Instrument MKTDoctors/1000Pop across US Counties (2019)



Additional Figures: Opioid Death Rates Over Time



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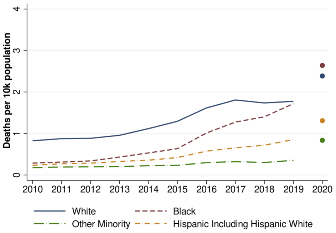
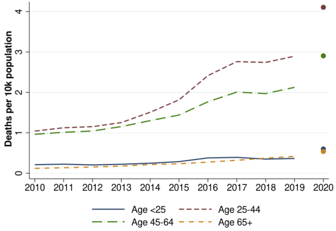
Additional Figures: Opioid Death Rates By Demographics

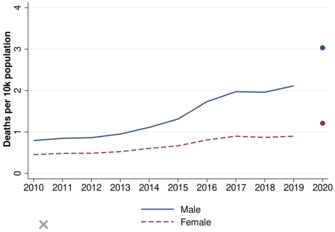
Panel A. Opioid Death Rates by Consumer Race



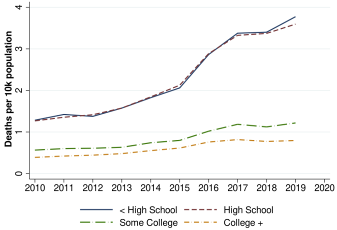
Panel B. Opioid Death Rates by Consumer Age



Panel C. Opioid Death Rates by Consumer Gender



Panel D. Opioid Death Rates by Consumer Education



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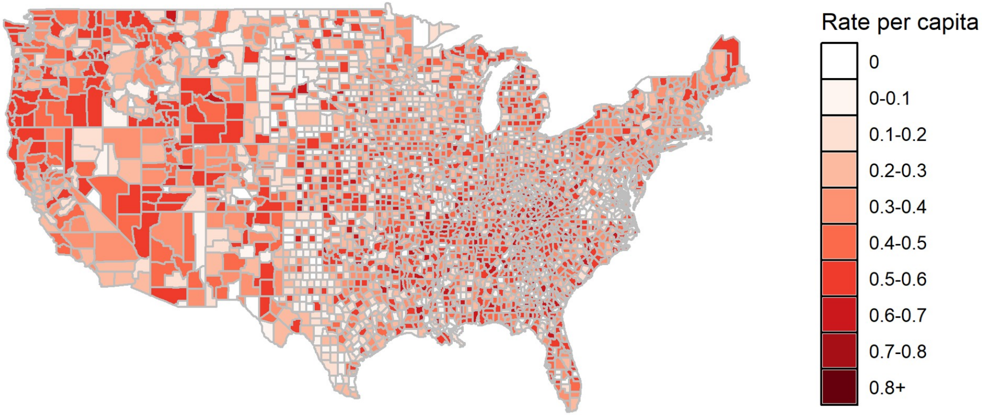
Additional Figures: Prescription Rates across US Counties (2019)



Additional Figures: Instrument MKTDoctors/1000Pop across US Counties (2019)