Opioid Epidemic and Mortgage Default[*]

Tural Karimli[†]

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Abstract

I document that the opioid epidemic causes mortgage defaults to rise in the United States, exploiting a plausibly exogenous adverse shock to the supply of prescription opioids (through abuse-deterrent reformulation of OxyContin). I present evidence that depressed local house prices, resulting from the epidemic, have caused more defaults through the home equity channel. Correspondingly, I show that lenders approve fewer loans to opioid-afflicted areas, indicating elevated search frictions for the constrained households living in these neighborhoods. In contrast, income or unemployment growth rates are not explanatory mechanisms for this effect.

Keywords: Opioid epidemic, oxycodone, mortgage default, delinquency rate, home equity

JEL: G51, I12, G21

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[†]Frankfurt School of Finance & Management. ✉ t.karimli@fs.de.

1 Introduction

Prescription opioids have led to the most significant health crisis in the United States preceding COVID-19 and reached epidemic levels; nearly 500,000 people lost their lives due to the opioid drugs (CDC, 2021). The Council of Economic Advisers estimates that the total economic cost of the opioid epidemic was at $696 billion alone in 2018 (3.4% of the U.S. GDP). The breadth and acceleration in opioid abuse and overdose mortality rates despite preventive regulatory measures pose several questions about the economic well-being of households[1].

In this paper, I study the effect of the opioid epidemic on household mortgage payment behavior and explore the underlying mechanisms of this effect. I document a significant positive economic impact on the mortgage default rates with the increasing rate of the local opioid crisis. Although one could presume that defaults are due to the loss of job or income as a direct propagator, the novel feature I demonstrate is that the spillover channel is the primary mediator. More precisely, I show that decreasing house values due to rising negative externalities in the opioid-afflicted areas squeezes households' current home equity, triggering defaults being originated from borrowers' strategic motives or constrained liquidity positions.

For my analysis, I employ county-level overdose mortality due to opioid drugs to measure the local opioid epidemic (Alpert et al., 2021, 2018; Evans et al., 2019). I combine this county-level measure of an opioid crisis with a rich census tract-level mortgage performance data set. Mortgage data covers conventional (i.e., securitized by Fannie Mae and Freddie Mac) loans originated between 2003 and 2017 and contains dynamic information on borrowers' payment history and credit risk measures (debt-to-income ratio, credit score, loan-to-value ratio, and income level) recorded at the time of loan origination. I then examine the effect of changes in the opioid epidemic on households' mortgage defaults, specifically delinquency rates (90 or more consecutive days missed payments, Bhutta et al. (2017); Ganong and Noel (2020); Low (2021)).

[1]There is growing literature on the economic consequences of the opioid epidemic, with a special focus on labor supply. For example, Krueger (2016); Aliprantis et al. (2019); Park and Powell (2021) document the significant negative impact of opioid abuse on the labor force participation rates in the United States.

Although we can observe a positive relationship between the opioid epidemic and mortgage defaults, the impact's direction is unclear. On the one hand, people who live in economic despair and have difficulties meeting their mortgage payments may increase demand for opioids, which then can result in more drug abuses and overdoses (Case and Deaton, 2017). On the other hand, borrowers might be exposed to the epidemic directly or indirectly because of the supply-driven opioid abuse and consequently default on the loans.

To address the endogeneity challenges born by reverse causality described above or unobservables in examining the epidemic's impact on the households' defaults, I employ an instrumental variable approach. I instrument for changes in opioid overdose death rates using the 2010 introduction of the abuse-deterrent version of OxyContin, the brand of opioid made by Purdue Pharmaceutical. OxyContin is a morphine-like narcotic painkiller drug with a slow-release formulation of oxycodone and has played a key role in the evolution of the prescription opioid epidemic (Alpert et al., 2021). The original version could be crushed or dissolved without any effort, and abusers could snort or inject to obtain high dosages of oxycodone. In 2010, Purdue Pharma reformulated Oxycontin to an abuse-deterrent version, which made it complicated and costly to dissolve and use for non-medical purposes. Since the reformulation is a nationwide shock, I interact the instrument with pre-2010 oxycodone exposure following (Alpert et al., 2018; Evans et al., 2019), who show that the supply disruption in prescription opioid has led to ignition in illicit (e.g., heroin and fentanyl) opioid overdose mortalities.

I start the analysis by investigating the effect of plausibly exogenous changes in the opioid overdose death rates on households' defaults. I provide strong evidence that the increased opioid epidemic has a significant positive impact on the mortgage delinquency rates, even after accounting for a rich set of borrower characteristics, fixed county conditions and trends, and local socio-economic factors. In particular, one standard deviation exogenous increase in opioid drug overdose mortality rises 90+ consecutive days delinquency rate by 3-4 percentage points on average. I carry out a number of sensitivity tests and confirm the robustness of the baseline against multiple alternative explanations. For example, I narrow down the underlying causes of opioid overdose death rates into prescription and illicit opioid drugs to validate the instrumental variable. In line with the earlier conjecture that OxyContin reformulation has led to substitution for illegal drugs, I demonstrate that the effect of the opioid epidemic on the defaults is due to the illicit opioid overdose death rates. In particular, given that the economic magnitudes are similar under this setting to the ones from baseline analysis reassures that effect is not an artifact of local unobservables. I also verify that the financial crisis does not contaminate the results by excluding the recession period from the analysis.

Having established robust positive effects of the opioid epidemic on households' mortgage defaults, I next proceed with analyzing the underlying economic forces of this result. Literature on the sources of mortgage defaults distinguishes two primary - direct liquidity and indirect home equity - channels (Foote and Willen, 2018; Ganong and Noel, 2020; Low, 2021). Analogously, the defaults due to the opioid epidemic may propagate through one of these main economic links. One example of a direct mechanism is when a borrower defaults as a result of death by drug overdose, causing an immediate liquidity shock within the household. Observing how such direct shocks manifest can be more challenging if the borrower is faced with slowly deteriorating health conditions due to drug abuse. People who are addicted to and abuse opioids may experience behavioral changes and weigh the present circumstances as more important than those in the future, leading them to spend more on drugs now, rather than paying the mortgage to secure their house for the future, due to the self-control issues (Ben-David and Bos, 2021; Ericson and Laibson, 2019; Schilbach, 2019).

To examine the role of the liquidity shocks caused by a loss of physical and mental health, I study the role of income losses and dropouts from the labor markets. Previous literature on the economic effects of the opioid crisis documents decreases in participation rates in labor markets (Krueger, 2016; Aliprantis et al., 2019; Park and Powell, 2021). However, various analyses using changes in aggregate household income and labor market participation rates do not indicate any role of such direct liquidity shocks in driving the default caused by the opioid crisis.

Indirect or spillover mechanism aligns with the lower home equity channel, where the household defaults as negative externalities drive down house prices to the point where paying the mortgage may no longer maximize household wealth, or simply due to borrowers finding that a lower level of home equity becomes a credit constraint. When households are exposed to adverse health shocks or need to finance some other activities (e.g., university tuition, entrepreneurship), home equity can act as a liquidity buffer (Gupta et al., 2018; Schmalz et al., 2017). More equity can alleviate the payment challenges, and households can quickly sell, refinance or apply for a home equity line of credit. On the other hand, families who find themselves over-burdened with debt due to the negative spillovers of the opioid epidemic may default strategically (Bhutta et al., 2017). Initially, I present that the epidemic has significant negative economic effects on the local house price growth rates, in line with the results provided by D'Lima and Thibodeau (2022) and Custodio et al. (2021).

Following the depreciating house values, I document that depending on current home equity, there are large differences in the effects of the opioid crisis on default rates. To be more precise, I demonstrate that the economic magnitudes for the loans with less than 20-40% current home equity are about eight or ten times larger than for the loans with current loan to value ratios below 60%. Observed small effects for the mortgage delinquency rates with higher home equity speak to the role of the direct effects in the absence of adverse spillovers. However, larger effects with lower home equity indicate the dominating role of the spillover channel.

Another essential dimension to consider in driving mortgage defaults through the indirect channel is banks' lending behavior in opioid-afflicted areas. Although banks cannot directly observe households' health backgrounds on opioid use, they can be more conservative in their mortgage origination to opioid-hit neighborhoods as risks are increasing in the housing markets. In particular, I document that banks significantly decrease both home purchase and refinancing loan originations. Lowering home purchases may further magnify depreciation in the house values, but the inability to refinance can directly result in defaults.

I contribute to three strands of economic literature. The first is on the financial market impacts of the opioid epidemic. These include works by Cornaggia et al. (2021); Li and Zhu (2019) on municipal finance; Ouimet et al. (2020) on firm growth; Custodio et al. (2021) and D'Lima and Thibodeau (2022) on real estate prices; and Jansen (2019) on defaults in the subprime auto loan market. My analysis is closely related to the work by Jansen (2019) and complements it in several ways. First, I extend the analysis to the mortgage market, focusing on high-quality loans, whereas Jansen's work is on the subprime auto-loan market. Hence, the results indicate that the epidemic's costs are much higher and not specific to financially fragile households.

Moreover, another essential part of my empirical analysis is an extensive analysis to understand how the opioid epidemic propagates, and I show that defaults are primarily driven by indirect channels, whereas Jansen's work emphasizes the role of direct mechanism. My paper is also related to the recent study by Cornaggia et al. (2021), who show that credit ratings are not predictive of risks related to the epidemic and provide evidence on credit cuts to municipalities in opioid-hit areas. Finally, my paper is also related to the works by D'Lima and Thibodeau (2022) and Custodio et al. (2021), who study the impact of the opioid crisis on local house prices. D'Lima and Thibodeau (2022) show that house prices drop as demand for houses in these neighborhoods decreases. Custodio et al. (2021) argue that increasing defaults also depresses local house prices. Although past defaults may be contagious and drive current bankruptcy rates, I show that house prices have been going down in these neighborhoods even after controlling for past delinquency rates.

My work also links to the small but emerging literature that studies the impact of health shocks on households' financial health. For example, Gupta et al. (2018) examines cancer diagnoses and the role of home equity, and Dobkin et al. (2018) estimates the economic costs of hospital admissions. Finally, the results of this analysis relate to the larger yet growing literature on the drivers of mortgage default (Campbell and Cocco, 2015; Bradley et al., 2015; Foote and Willen, 2018; Ganong and Noel, 2020; Low, 2021).

This paper is structured as follows: Section 2 gives brief institutional information and an historical perspective on the opioids crisis; Section 3 describes the data; Section 4 provides the estimation strategy and discusses the results of the effect of the opioids crisis on households' mortgage defaults; Section 5 investigates possible underlying economic mechanisms; Section 6 is the conclusion.

2 Background on the Opioid Epidemic

The roots of the current US opioid crisis dates back to the 1980s. The experiment conducted by Portenoy and Foley (1986) to analyze the long-term usage effects of opioid pain killers (based on 38 chronic pain patients) concluded that opioid maintenance therapy can be safe. These results were then widely used to support the use of opioid painkillers for non-cancer pain. Around the same time, the medical community in the United States started exerting pressure in favor of an aggressive approach to deal with chronic pain. Hence, the practice to prescribe opioid pain killers to cure chronic non-cancer pain gradually increased, and then accelerated rapidly following the 1995 FDA approval of ”OxyContin” (a slow release formulation of oxycodone) by the pharmaceutical company Purdue Pharma.

Based on the conclusions made by Portenoy and Foley (1986), Purdue Pharma deployed aggressive marketing strategies to spread the message that OxyContin was safe and non-addictive because of its slow-release mechanism. Purdue Pharma gave instructions to its sales representatives to convince doctors that ”fewer than one percent” of patients who took OxyContin had become addicted (The New Yorker, 2017)[2]. According to the United States General Accounting Office (2003), from 1996 (the year that OxyContin was launched) to July 2002, Purdue Pharma funded over 20,000 pain-related educational programs through direct sponsorship or financial grants[3]. Purdue Pharma's aggressive advertising and promotion strategies resulted in enormous growth in its revenues from $48 million in 1996 to $ 31 billion in 2016[4]. In 2007, Purdue Pharma was accused by the Federal Drug Administration (FDA) of misleading the public about OxyContin's addiction risk, and the company agreed to pay $600 million in fines. In 2010, Purdue Pharma reformulated OxyContin to an abuse-deterrent formulation to reduce levels of abuse. Although Oxycontin use and shipments of oxycodone dropped following this reformulation, heroin use and heroin overdose rates concurrently increased in areas with higher earlier exposure to the prescriptions opioids documented by Alpert et al. (2018) and Evans et al. (2019). By 2019, 36 states filed lawsuits accusing the company of false advertising, and Purdue agreed to pay $10 billion to settle the claims.[5] In September 2019, Purdue Pharma filed for Chapter 11 bankruptcy.

Besides the impact of the aggressive marketing and promotional activity by Purdue Pharma, a changing institutional environment has also played a significant role in the widespread pre-

[2]https://www.newyorker.com/magazine/2017/10/30/the-family-that-built-an-empire-of-pain
[3]https://www.gao.gov/htext/d04110.html
[4]https://www.latimes.com/projects/oxycontin-part1/
[5]https://www.ft.com/content/0b9adde2-8485-45e9-a896-86e63ac00d72

scription of opioids by doctors. Upon the launch of OxyContin in 1995, the American Pain Society launched a campaign entitled, ”Pain is the Fifth Vital Sign”, and, according to Kolodny et al. (2015) this further encouraged higher prescription of opioids to treat non-cancer chronic pain. In 2001, the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) decided to add pain as the fifth vital sign in the physician checklist, along with body temperature, blood pressure, heart rate, and respiratory rate Pacula and Powell (2018).

As the negative consequences of the widespread use of prescription opioids increased, concerns about its defectiveness became more common into the 2000s. On top of lawsuits against pharmaceutical companies, public institutions determined new standards and states made interventions. In 2014, the Agency for Healthcare Research and Quality (AHRQ) announced that the evidence on the effectiveness of prescription opioids to treat chronic non-cancer pain was insufficient. In 2017, The CDC determined new standards to cure non-terminal pain.

3 Data and Main Variables

I combine data sets from multiple sources to estimate the impact of the opioid epidemic on the mortgage market. These data sets are i) opioid overdose death rates, ii) prescription opioid supply, iii) mortgage origination and performance, iv) various sources for local demographic and economic characteristics. I conduct the main analysis for the 2004-2017 period as it allows me to employ the 2010 OxyContin reformulation shock as an instrument for the opioid mortality rates. All the outcome and control variables for the mortgage market are constructed at the census tract level, which I describe below, where I also provide details about each source and the variable construction.

3.1 Opioid Mortality

The Multiple Cause of Death database by the Center for Disease and Control (CDC)[6] provides mortality data for all US counties, based on death certificates, which provides information on a single cause of death, up to twenty underlying causes of death. Using this database, I categorize

[6] https://wonder.cdc.gov/mcd-icd10.html

opioid-related mortality using ICD-10 codes. Following the previous studies on the opioids crisis, I construct two proxies for opioid epidemic based on drug overdose death rates: *Total OD* and *Opioids OD*. I define *Total OD* if the overdose mortality is due to one of the following ICD-10 codes: X40 - X44, X60 - X64, X85, and Y10 - Y14, and *Opioid OD* if the overdose mortality is due to one of the following drug poisonings: T40.0 (opium), T40.1 (heroin), T40.2 (other opioids, e.g. oxycodone, hydrocodone), T40.3 (methadone), and T40.4 (other synthetic narcotics, e.g. fentanyl). The advantage of using total drug overdose measures on the top of overdoses related directly to opioids is that opioid overdose as a cause of death is more likely under-reported on the death certificates. The CDC does not publish the numbers for the counties which experience fewer than ten deaths for a given category of death. For the purposes of my analysis, I further group $Opioid\ OD$ into two groups: presciption opioid overdoses ($Prescription\ OD$) based on ICD-10 codes T40.2 and T40.3, and illicit opioid overdoses ($Illicit\ OD$) based on ICD-10 codes T40.0, T40.1 and T40.4.

At the final stage, I normalize all measures per 100,000 people for a given county using the county population provided by this database. Figure 1 illustrates the distribution of mean $TotalOD$ across the United States, and also pictures the total coverage of the counties that my analysis relies on. Figure 2 provides the national trend in opioid overdose rates. It clearly shows the two phases of the epidemic; the first from prescription opioids, which stagnated in the oxycodone reformulation period, and the second phase starts in 2010 and is driven by the explosion of overdoses related to heroin and fentanyl.

3.2 Opioid supply

The Automated Reports and Consolidated Ordering System (ARCOS), maintained by the Drug Enforcement Administration (DEA), collects and provides reports on retail distribution (by total weight in grams) of controlled substances (e.g., oxycodone, hydrocodone, fentanyl, etc.). A restricted version of the ACROS data[7] for years 2006-2014 has become available at the result of legal actions taken by The Washington Post and the Charleston Gazette-Mail of West Virginia[8].

[7] Available at https://www.slcg.com/

[8] https://www.washingtonpost.com/health/how-an-epic-legal-battle-brought-a-secret-drug-database-to-light/2019/08/02/3bc594ce-b3d4-11e9-951e-de024209545d_story.html

This is a large and rich dataset consisting of 500 millions transactions, which provides details about the manufacturers and buyers of these drugs (e.g., pharmacies, research institutions), the date of transactions, the state and county name of the buyer, the drug name, and the dosage units.

Using this database, I construct *Pre Oxy Supply* measure, calculated as the average oxycodone supply (in dosage units) by chain and retail pharmacies per capita for the years 2006-2009[9]. Here, I exclude other channels of supply like shipments to medical research institutions, following Cornaggia et al. (2021), to focus on the distributions to the consumers. I use average county population estimates for the same period from American Community Surveys to normalize oxycodone supply to per person, which formally can be shown as follows:

$$Pre\ Oxy\ Supply_j = \frac{\sum_{t=2006}^{T=2009} Oxycodone_{j,t}}{\sum_{t=2006}^{T=2009} Population_{j,t}}$$

where j stands for the counties.

3.3 Mortgage data

I use Fannie Mae and Freddie Mac's Single-Family Loan Level Data, which contain loan origination and performance-related information on high quality, fully amortizing, 15-40 years, fully documented, fixed-rate single-family mortgages. Fannie Mae and Freddie Mac are the two most prominent central players in the mortgage securitization market, often referred to as the "elephants in the room." During 2016 these government-backed securitization enterprises (GSEs) originated 45.9% of all-single family originations, and were holding 59.2% of outstanding mortgage back securities (MBSs) (Richardson et al., 2017). Since these datasets does not contain any geographical identifiers smaller than 3-digit zip codes, I use the Home Mortgage Disclosure Act (HMDA) loan application record (LAR) data sets, as in Adelino et al. (2016) and Saadi (2020), to identify the census tracts geo-ids for these loans. To identify the 3-digit ZIP code for each loan application in HMDA, I use USPS ZIP to Census tract crosswalk files from

[9]The results of analysis is robust to using the exposure only as of 2006, and also measuring oxycodone in grams. Tables are available upon request.

the U.S. Department of Housing and Urban Development (HUD) office for 2000 and 2010 census tract definitions. Before matching the geo-correspondence files, I make sure that at least 70 percent of the population within a census tract lives within the given 3-digit zip code using population weights. Since HMDA uses the 2000 census tract definition in the LAR data sets for years 2003-2011, and the 2010 definitions from 2012 to the present, I match the census tracts with the respective geo-correspondence files. For the objective of my analysis, in HMDA I consider the originated mortgages to be the primary residence of the borrowers. After having 3-digit zip codes for each loan application, I match the HMDA data to the Fannie Mae and Freddie Mac loan performance datasets, based on the following identifiers: origination year, 3-digit ZIP code, loan acquirer (Fannie Mae or Freddie Mac), loan purpose (home purchase or refinancing), loan amount. Following Saadi (2020), I keep unique matches (i.e, one loan id for one geo id) to ensure that the census tract for a given loan is correctly matched. At the final stage, I crosswalk 2000 tract IDs to 2010 IDs using the tract relationship file from the Census[10]. Overall, I obtain 69,753 unique tract IDs before conducting any further data merges (there are 74,134 tracts in the 2010 Census).

Loan performance files indicate how long the borrower has been missing payments. Using this information, I construct two classic mortgage default measures, *60+ days* and *90+ days delinquency rate*, which indicate whether a borrower has been missing payments for at least two and three months consecutively. To build these measures, I assign a value of one to the delinquent loans and zero otherwise. Then, I aggregate these measures to the census tract and year level across all mortgage cohorts[11] and originators. Next, I compare constructed default rate to the same measure by Consumer Finance Protection Bureau (CFPB) in Figure A1, which shows a correlation of 76%. Unfortunately, CFPB publishes the data only for 471 counties out of 3006 and starts from 2008, making it impossible to fit into my analysis setting as drug overdose rates are not available for all counties.

[10]For precise mapping, I ensure that the given tract area contains at least 60% of 2000 and 2010 tract definition population.

[11]With this procedure, delinquency rates are based on more loan cohorts as we move into the recent years. For example, the 2004 delinquency rate reflects the performance of the 2003 and 2004 loan cohorts. Later in the analysis section, I carry out the analysis with the cohort dimension and find similar effects.

Moreover, I build tract-level borrower creditworthiness variables based on loan origination data sets by the GSEs and HMDA. These are a debt-to-income ratio, loan-to-value ratio, credit score, interest rates, and applicant's income at the time of the loan origination. Finally, I trim all the mortgage-specific variables at five percentiles by year in order to avoid outliers for the final analysis.

3.4 Data on demographic and economic environment

I collect tract population, housing units, insured population rate from the Census, house price growth rates from the Federal Housing Finance Agency and Zillow, household income from the Internal Revenue Service, labor force participation from the Bureau of Labor Statistics, cancer mortality rate from the CDC, and the number of hospitals from the Area Health Resources Files. Summary statistics for the variables employed in the main analysis is reported in Table 1.

4 Effect of Opioid Epidemic on Mortgage Defaults

Identifying the impact of the opioid epidemic on household mortgage payment behavior is not a straightforward task, although one can guess that there is a positive correlation. It is possible that economic hardships may lead to the use of opioid drugs, and also some fixed borrower characteristics may be the source of such positive comovement. The ideal setting would be comparing two borrower groups with similar socio-economic status and chronic pain issues, where one group is treated randomly with addictive opioids. The important assumption in this setting would be that there is no spillover effect from the borrowers who start abusing the opioids on other borrowers. However, it is hard to sustain such an assumption in my setting as negative externalities (see Mallatt (2019), for heroin dealership crime) may affect others living in the same community. However, since it is impossible to observe which borrowers have pain-related health issues, and who among them are prescribed with opioid drugs, I analyze it at the census-tract level and deliver the overall effect of the epidemic on mortgage defaults.

Since the rise in overdose rates and delays in mortgage repayments can be due to many unobservable economic factors, it is essential to identify an exogenous shift in overdose mortality rates. In 2010, Purdue Pharma reformulated OxyContin to an abuse-deterrent version, since the earlier version of this drug was easy to dissolve and intake high doses of oxycodone all at once.[12] The new version limits the opportunities for abuse but preserves the pain-relieving benefits for medical use. Using data from the National Survey on Drug Use and Health (NSDUH), Alpert et al. (2018) document a 40% decline in self-reported misuse of OxyContin between 2010 and 2014. At the same time, based on the same survey, Cho et al. (2021) show that the number of self-reported heroin users increased from 1.7 million in 2007 to 5.4 million in 2017. Medical literature also documents a rise in heroin use among patients with a history of OxyContin abuse after the OxyContin reformulation in substance abuse programs (Cicero and Ellis, 2015).

Exploiting this structural change, Evans et al. (2019) and Alpert et al. (2018) show that the states with higher levels of OxyContin misuse before the reformulation have experienced higher rates of heroin overdose. Hence the supply shock, caused by the reformulation, in the presence of close substitutes, failed to reverse the trend, but rather led to an unintended inflation in overdose rates. This literature documents that the trend in heroin-related overdose rates in high and low oxycodone exposure areas were similar before the reformulation of OxyContin. Since the OxyContin reformulation was a nation-wide event, I also use earlier exposure rates to OxyContin, using the local oxycodone[13] supply rate described in Section 3. Employing a similar setting for the first stage of instrumental analysis, but measuring the oxycodone supply at a more granular level, I estimate the following two stage least squares model to identify the impact of the opioid epidemic on the mortgage defaults in my setting:

$$Drug\ OD_{j,t-1} = \alpha_j + \nu_t + \gamma \cdot Oxy\ Reform_t \cdot Pre\ Oxy\ Supply_j + \Gamma \cdot X_{i,t-1} + \epsilon_{i,t-1} \quad (1)$$

$$Delinquency\ Rate_{i,t} = \alpha_j + \nu_t + \theta \cdot \widehat{Drug\ OD}_{j,t-1} + \Omega \cdot X_{i,t-1} + \eta_{i,t} \quad (2)$$

Here, i, j, and t are tract, county, and year indices respectively. a_j and ν_t stand for county and year fixed effects, respectively. $Oxy\ Reform_t$ is an indicator variable that takes the value

[12] Origins of an Epidemic: Purdue Pharma Knew Its Opioids Were Widely Abused: https://www.nytimes.com/2018/05/29/health/purdue-opioids-oxycontin.html

[13] OxyContin brand is a slow release formulation of oxycodone.

of 1 for the years 2011-2017 and 0 for 2004-2010 [14]. $Pre\ Oxy\ Supply_j$ captures the exposure of counties to oxycodone supply in the pre-treatment period (supply of oxycodone dosage units through chain and retail pharmacies per capita for 2006-2009).

The main outcome variable of interest here is *delinquency rate*, which measures households' default at the census tract level, computed as the share of borrowers who have missed the mortgage payments for either 60+ days or 90+ days among all borrowers in a given census tract and year. To proxy the local opioid epidemic, I use the total drug and opioid-related overdose mortality rates, a direct measure of misuse or abuse of opioid drugs. Another alternative measure would be local doctor shopping, which could proxy abuse. However, proxies like local prescription rates do not naturally capture abuse as it only considers the number of prescriptions dispensed per capita on average, not its addictiveness or overuse. Besides, it can also generate positive effects in the short horizon if used properly for medical purposes. *Overdose deaths* stands out as the most relevant local opioid epidemic variable for my research objective.

In all specifications, I also include, as of mortgage origination period, borrower characteristics as controls to capture local creditworthiness, to avoid the possible selection and omitted variable issues. For instance, credit scores, interest rates, and loan-to-value ratios, to some extent, can capture borrowers' risk-taking behavior, which can drive both default and opioid misuse. Moreover, assuming the banks are aware of such risks, they should be captured in the origination interest rates. I also include variables to control the local economic and demographic environment, which may correlate with both outcome and explanatory variables of interest. For instance, a deterioration in the local economic climate might lead to more drug use and a greater number of defaults. Note that a strong painkiller such as OxyContin is also widely used to treat pain among cancer patients. To mitigate concerns about the violation of exclusion restriction, I also control for the cancer mortality rate, along with other covariates. Additionally, I lag the explanatory variable of interest and all the other controls by one year to alleviate possible reverse causality concerns, as difficulty with meeting payments could also lead to adverse health. Finally, I cluster standard errors at the county level to correct for the within-county and across-year correlations.

[14] Purdue Pharma released the reformulated OxyContin in August, 2010. For brevity, I assign 2010 to the control period, my results are also robust to the exclusion of 2010.

In Table 2, I report the results on the main specification. First stage estimates in Panel A indicate a strong statistical and economic relevance of the instrument across both measures of overdose mortality. Consistent with earlier literature, I document that total drug and opioid overdoses rates increase in response to the OxyContin reformulation in counties with higher oxycodone exposure. Thus, the net effect of the reformulation has not been null but was exacerbating to the opioid crisis. Having a similar impact on both proxies for the opioid epidemic points to the same source of ignition. These results indicate that total drug overdose mortality is driven primarily by opioid-related overdose rates.

The coefficients on the instrumented overdose mortalities in Panel B indicate an economically meaningful and statistically robust positive causal link between the opioid epidemic and mortgage defaults. Results under this specification suggest that a one standard deviation change in drug mortality rates results in an approximately 3-4 percentage points increase in local delinquency rates. This is a substantial effect given the average delinquency rate in my sample is around 3-4%, and households' total mortgage debt in the United States is well above $11 trillion[15]. When defaulting leads to foreclosure, this not only wipes out borrowers' housing wealth, but also affect real outcomes and generates substantial risk for the financial institutions in the mortgage market.

To test the validity of the instrumental variable, I conduct placebo tests using prescription and illicit opioid overdose death rates. Again, the underlying hypothesis has been that the reformulation caused people with an addiction to the prescription drugs to substitute them for illicit ones from the streets. In Panel A, in Table 3, , I show that this shock did not result in any changes in the prescription opioid overdose rate. Consequently, there is no effect on the rate of default. In contrast, the estimates on *Illicit OD* indicate an almost one-to-one mapping to economic magnitudes in the main results. Firstly, we can see that the increase in opioid drug overdose rates in response to the disruption in the OxyContin supply comes entirely from illicit drug overdoses, echoing the findings of Evans et al. (2019), Alpert et al. (2018) and Park and Powell (2021). More importantly, the effect of illicit drug overdoses on the default rates is similar in both economic and statistical magnitudes to total drug death rates, suggesting the

[15] https://www.newyorkfed.org/newsevents/news/research/2022/20220510

instrument is not producing the results because of artefacts of data construction or estimation methods.

Since the OxyContin reformulation overlaps with a recession, it can be argued that such an economic downturn led to worse living standards, the higher use of opioid drugs, and more defaults. To evaluate whether such reverse causality impacts my results, I estimate the baseline model having completely excluded the recession period of 2008-2011 when the default rates were picked. As a result, the output in Table A1 presents almost the same coefficients as in the baseline setting, ruling out any such contamination.

In constructing the mortgage data set, I take the mean of default measures by census tract and year, leaving out the loan cohort dimension. The effect may be borne by the loan cohorts in the pre-financial crisis when the loan origination standards were softer. Haughwout et al. (2008) document that the performance of loans originated in 2005-2007 was worse than the 2001-2004 loans over the one-year horizon. Median credit scores at the loan origination period are 721 and 755 in pre- and post-financial crisis periods, respectively, in my sample, indicating a transition towards even more prime borrowers in the GSEs' securitization of loans. Moreover, such a procedure in calculating default rates does not allow me to control for the loan age, which may play a substantial role in borrowers' default decisions. To address these concerns, I expand the mortgage performance data set by including the cohort dimension, allowing me to utilize $Cohort \times Year$ fixed effects, which absorbs average differences over the sample period in the loan performance coming from vintage periods or loan age. For comparability to baseline results and specification, I initially estimate the effect using only county and year fixed effects, and next, I replace year dummies with $Cohort \times Year$ dummies. As illustrated in Table A2, under both specifications, I observe statistically and economically similar effects to my main results, giving me the confidence to argue that the documented salient impact is not a manifestation of a spurious relationship arising from endogenous borrower characteristics.

One possible alternative explanation along the lines of reverse causality is that the effect is coming from regions with a historical connection to other narcotic drugs that have been experiencing even worse economic outcomes. One such region that was hit hard by the opioid crisis is the Appalachian communities[16]. To test whether such long historical memory inflates the documented results, I exclude these counties from the main sample and rerun the baseline specification. The estimation output reported in Table A3 shows the impact of the opioid crisis on mortgage default becomes even more slightly pronounced, ruling out biases due to the prior illegal drug use.

Although the various analyses above cover the issue of the effect resulting from previous economic hardships, I directly address this concern using different measures for local despair in sample-split setting, specifically manufacturing employment (US Census), poverty (US Census) and subprime population rates (FRED St. Louis) for the 2001-2005 period. A noteworthy feature of the manufacturing employment measure is that it does not only capture loss of jobs in this sector due to the increasing competition from imported goods, it also reveals that people working in manufacturing are more likely to suffer work-related injuries. To proceed with the hypothesis that high levels of economic despair lead to drug abuse and consequential defaults, I cut sample into two, based the median of three proxies, namely areas with above and below median manufacturing employment, poverty, and low credit score population rates, and repeat the main estimation across the six sub-samples. The output is shown in Table 4 and suggests that lower historical levels of economic well-being do not lead to endogeneity issues and spurious coefficients.

The literature on the evolution of the opioid epidemic emphasizes the role of the supply factors, such as the deceptive marketing tactics by Purdue Pharma (Alpert et al., 2021), and physicians' pain treatment preferences (Finkelstein et al., 2018). Since these drugs are usually distributed through by physicians, having health insurance can make access to opioids easier. Another important trend during this period, as documented by the Council of Economic Advisers, is that the share of prescription opioids subsidized by public insurance schemes has been increasing (from 17% in 2001 to 63% in 2015)[17], making prescription opioids cheaper on the streets as compared to illegal narcotics. Thus, in highly insured areas, patients may have more propensity to be prescribed such drugs, or may lead to prescription opioids flowing into

[16] https://www.arc.gov/map/subregions-in-appalachia/

[17] https://trumpwhitehouse.archives.gov/wp-content/uploads/2019/04/The-Role-of-Opioid-Prices-in-the-Evolving-Opioid-Crisis.pdf

the black market. To test this conjecture, I collect per capita insurance rates data from the Census. The data is only available from 2006, preventing me from going further back into the early 2000s. I again divide the sample into two by median insurance rate, and re-estimate model 1. In line with the suggested hypothesis, I find that effect is only significant in highly insured areas, allowing me to argue that the lack of insurance does not play any meaningful role in driving the effect.

During the OxyContin reformulation period, another salient legislation in the opioid environment was passed in Florida. As a result, between 2010 and 2011, Florida shut down 'pill mills' that were distributing prescription opioid drugs in large quantities. Given that such regulation could also lead to unintended consequences, this could skew the results with regard to the reformulation event. To circumvent this issue, I dropped Florida from the analysis and found a similar and slightly lower effect tabulated in Table A4. Hence, such contamination does not affect the main findings in any meaningful way.

Across all estimations to proxy the mortgage default rate, I have been using either 60+ or 90+ days delinquency rates. It is more relevant to use these measures for my analysis since the borrowers are the ones taking the action by choosing not to pay, whereas the foreclosure rate depends on actions by the lender (Bhutta et al., 2017). Nevertheless, I examine the robustness of the main results using two alternative default measures, namely the delinquency rate, once again, this time with delayed payments of at least 120 days, and the foreclosure rate. I infer foreclosure from the zero-balance status of the loan. If the loan balance becomes zero due to a credit event as reported in the loan performance data set, I consider it to be foreclosed. Using this information, I construct tract level foreclosure rate for a given year measured as the number of loans foreclosed by the number of all outstanding mortgages. The estimation output is given in Table A5, using these proxies, once again show the statistically and economically significant impact of the epidemic on default rates. Note that, although the effect is smaller when the foreclosure rate is used as a proxy for default, relative to its mean (0.3%), the effect is even much larger.

5 Economic Mechanisms

The economic mechanism behind defaults resulting from the opioid epidemic can be realized in two ways: through direct and indirect (spillover) channels. In the direct scenario, defaults can occur if the borrowers are directly exposed to such drugs. In the latter case, defaults arise if the opioid epidemic causes negative spillovers, triggering defaults through the home equity channel. If borrowers' current employment status and income levels were observable to the econometrician, it would have been possible to disentangle these two channels and discover which is dominant. However, for my analysis, I will employ such measures at the county level and show which mechanism is propagating the relationship between the opioid epidemic and mortgage default at the aggregate level.

Direct exposure to opioid drugs may drive mortgage defaults if the borrower dies due to the overdosing. A recent study by Low (2021) shows that illness, disability, or death have been one of the major drivers of mortgage default, explaining more than 40% of all defaults with payment difficulties. Thus, death itself can explain the mechanical relationship between the opioid epidemic and mortgage defaults as a source of liquidity shock. However, overdosing and resulting deaths happen at the extreme levels of addiction. Addiction to such drugs and abusing them over a longer time horizon can lead to behavioral changes. Intertemporal preferences can change, and consuming more drugs now become more important to the user than consuming other goods in the future. Ben-David and Bos (2021) show that the availability of alcohol increases impulsive consumption and causes more financial distress. Given that addiction to opioid drugs is very likely if used in high doses, abusive behavior will be more likely. Consequently, deteriorating health conditions can lead to liquidity shocks if they result in a loss of income or employment opportunities. Indeed, several studies document negative consequences of the opioid epidemic on labor force participation rates (Park and Powell, 2021; Aliprantis et al., 2019; Krueger, 2016).

To understand the role of such liquidity shocks, I conduct various analyses in sample split settings. Initially, I examine whether dropouts from the labor market offer any suggestive indications to explain the effect of the opioid epidemic on mortgage defaults. To conduct this experiment, I collect annual county-level labor force participation growth rates ($\Delta LFPR_t$) from the Bureau of Labor Statistics (BLS) since the borrowers' employment status is not observable, as mentioned above. Using this measure, I split the sample into two county groups, one below and one above the median labor force participation growth rate based on the distribution over the current year, and re-run baseline IV specification. The underlying hypothesis is that, if the opioid epidemic causes lower labor force participation, defaults should systematically be higher in areas with higher dropouts from the labor market. The output of this analysis is provided in Table 6. The coefficient on $Opioid\ OD$ is only significant in areas with lower labor supply growth. Nevertheless, the economic magnitude is much lower compared to the one for the higher labor supply growth sample given in column 3. Repeating the same analysis using $Total\ OD$ as a proxy for the epidemic delivers statistically significant coefficients in both samples and a yet stronger effect in the higher employment growth areas. Although given in this sample construction, I rely only on the distribution, not merely the dropouts from the labor market, and I re-build alternative sub-samples based on sign of labor force participation rate (i.e., counties with negative and positive $\Delta LFPR_t$) to further clarify the interpretation and provide insights into the role of job losses. The outputs tabulated in Table A6 indicate that the effect is only significant in counties with positive annual labor supply growth rates. Pooling the results of both exercises suggests that, at least at the county level, dropouts from the labor market due to the opioid epidemic cannot explain the mortgage defaults.

To further shed light on deteriorating health conditions and subsequent loss of liquidity, I implement analogous sample-split analysis using county-level household adjusted gross income growth rate data from the Internal Revenue Service (IRS). Similarly, I design the sub-samples based on the median of the annual income growth rates. If crisis areas experience lower cash flows (i.e., lower income growth) due to the health issues, it can ignite defaults as a direct source of illiquidity. Re-estimating the baseline model, I find economically similar results illustrated in Table 7 as in the labor supply study. Specifically, the estimates indicate that the effects are more pronounced in the higher income growth counties. Again, re-constructing the samples based on the sign of the income growth rate, I find that negative cash flows cannot explain defaults caused by the opioid epidemic reported in Table A7. Summarizing the evidence gathered on the role of labor supply and income growth rate suggests that such direct illiquidity shocks are not systematic propagators. However, the caveat is that these conclusions are driven solely based on county-level measures. Hence, there may be some biases in identifying the role of income shocks if they are more idiosyncratic than geographic. Nevertheless, given that the opioid epidemic is systemic, some indications in the direction of this mechanism should be observable.

An alternative economic mechanism that can trigger defaults in the face of a rising epidemic in the local communities can be an indirect one. Generally, such an epidemic may increase local despair through different forces. If local despair rises, it may be mirrored in local house prices and, consequently, in the home equity of the local borrowers, who are not abusing opioids. Defaults can be triggered by low levels of home equity, and even negative equity, in neighborhoods that are hit harder by the opioid epidemic. I look closely at three avenues to corroborate the role of the spillovers.

First, I directly examine the impact of the opioid crisis on local house prices. The concurrent literature (D'Lima and Thibodeau, 2022; Custodio et al., 2021) already include extensive analysis on this question and shows the epidemic moved house values downward. To study it for my research, I collect house price growth rates from the Federal Housing Finance Agency (FHFA), which is not available across the universe of all tracts. To supplement this, I also collect house prices from Zillow, but Zillow provides house values at the 5-digits zip code level. I crosswalk Zillow data to the tract level using HUD geo-correspondence files. Using both versions of the changes in house prices, I re-estimate the baseline model and provide the output in Table 8 in columns 1 and 2. Having similar economic magnitudes for Zillow and FHFA gives me the confidence to suggest that a one standard deviation increase in opioid drug overdoses decreases house prices by 8.6-8.8 percentage points. These estimates are similar to the ones provided by D'Lima and Thibodeau (2022). Custodio et al. (2021) argue that one of the main explanations for the house price depreciation in the opioid-afflicted areas is households' increasing defaults. If past defaults drive current defaults, this implies the role of neighborhood house prices as a mediator. At the same time, D'Lima and Thibodeau (2022)argue that decreasing demand for houses in opioid-hit areas drags down real estate values. To check the sensitivity of the coefficients on $Opioid\ OD$ in these estimations, I also include the lagged delinquency rate as a control. If the effect is due to the contagion in defaults, coefficients should be absorbed to an economically meaningful extent. However, columns 3 and 4 show only slight differences from the previous coefficients.

Provided that the opioid crisis negatively influences house prices, I continue with a closer examination of the role of home equity by computing the current mortgage loan balance to the current house value ($CLTV$) ratio for each outstanding mortgage, following a similar methodology as that used by (Bhutta et al., 2017). Although current loan balance is published in the mortgage performance data sets by Fannie Mae and Freddie Mac, house values are not directly observable. Therefor, I infer it from the published loan to value ratios and loan amounts reported at the time of loan origination, which allows me to observe house value only for this period. To calculate the current house value, I use county-level house price growth data from the Federal Housing Finance Agency (FHFA) since it is available for every county for the period of my analysis[18]. Finally, I construct each mortgage origination cohort's cumulative house price indices using this variable. In this way, I can observe house value appreciation (or depreciation) since the origination year for each mortgage.

To study whether the current home equity levels have any amplifying role, I draw on three loan samples based on their $CLTV$ ratios: loans with $CLTV$ below 60%, loans with $CLTV$ above 60%, and loans with CLTV above 80%. Thus, as an outcome variable of interest in these exercises, I employ three delinquency rates conditional on the cutoffs on CLTV . Running the benchmark model, I find striking differences in the effect of the epidemic on the defaults depending on the level of home equity given in Table 9. For the loans with $CLTV < 60\%$, the effect is about eight times lower than for the other side of the cutoff. The result is even more pronounced if current home equity is less than 20%, where refinancing options are even more squeezed. The rise in economic magnitude speaks to the increasing role of the externalities, such as a downturn in housing values. In other words, when there is enough home equity the effect can be attributed to specifically direct effects. The documented stronger effect with lower current home equity indicate that the indirect channel alone, or together with some source of liquidity shock, runs deeper.

[18]In untabulated results, I also use tract-level house prices and find similar effects.

Given that the current level of home equity reduces as homes lose value and risks rise in opioid-afflicted areas, we may expect banks to take precautionary steps and originate fewer loans in these neighborhoods. The opioid epidemic alone will feed into local credit risk metrics as banks cannot screen borrowers' health backgrounds. Rejecting mortgage loans can further contribute to the likelihood of defaults, which I will describe in more detail through the lenses of the analysis. First, to learn if banks are cautious and originate fewer mortgages to opioid afflicted areas, I construct a tract-level mortgage approval rate measure computed as the number of approved mortgage applications divided by the number of applications made. I find an economically significant effect in the loan approval rate on the local epidemic measures shown in Table 10. A one standard deviation increase in the epidemic leads to a 3.7-4.3 percentage points decrease in the overall application approval rate, after controlling for the observable credit risks for both applicant and locality. Such negative spillover can hurt the overall regional economic environment, not just the households with mortgages. To understand how mortgage rejections may trigger defaults, I examine the effect of the opioid crisis separately for home purchase and refinancing mortgage applications. The distinction between the two is essential in terms of their mediating roles. A large number of rejected home purchase loans will put further pressure on real estate values in that area, which will affect the home equities across the area, while frequent rejection of refinancing loan applications can directly affect the loan repayment performance, especially if the borrower is suffering from a liquidity constraint. Columns 3 and 4 show banks strictly cut home purchase loans to these areas as the opioid epidemic becomes more severe. We can also observe that such an effect is not unique to home purchase loans; banks also reduce the number of refinancing loans, making the search process for the borrowers burdensome.

The concluding message, based on all the evidence on the role of the different economic channels, is that externalities play a significant role in amplifying mortgage defaults caused by the opioid crisis.

6 Conclusion

This paper studies the impact of the opioid epidemic on mortgage defaults in the United States. Exploiting a plausibly exogeneous adverse shock to the supply of prescription opioids through the abuse-deterrent reformulation of OxyContin, I document that the opioid epidemic causes a rise in mortgage defaults. This relationship is more pronounced in areas with greater access to prescription drugs, but is unaffected by the levels of historical economic despair.

I present evidence that depressed local house prices, resulting from the epidemic, have caused more defaults through the home equity channel. Correspondingly, I show that lenders approve fewer loans to opioid-afflicted areas, indicating elevated search frictions for the constrained households living in these neighborhoods. In contrast, income or unemployment growth rates are not explanatory mechanisms for this effect. Overall, my findings contribute to the current discussions on the direct and indirect costs of the opioid epidemic.

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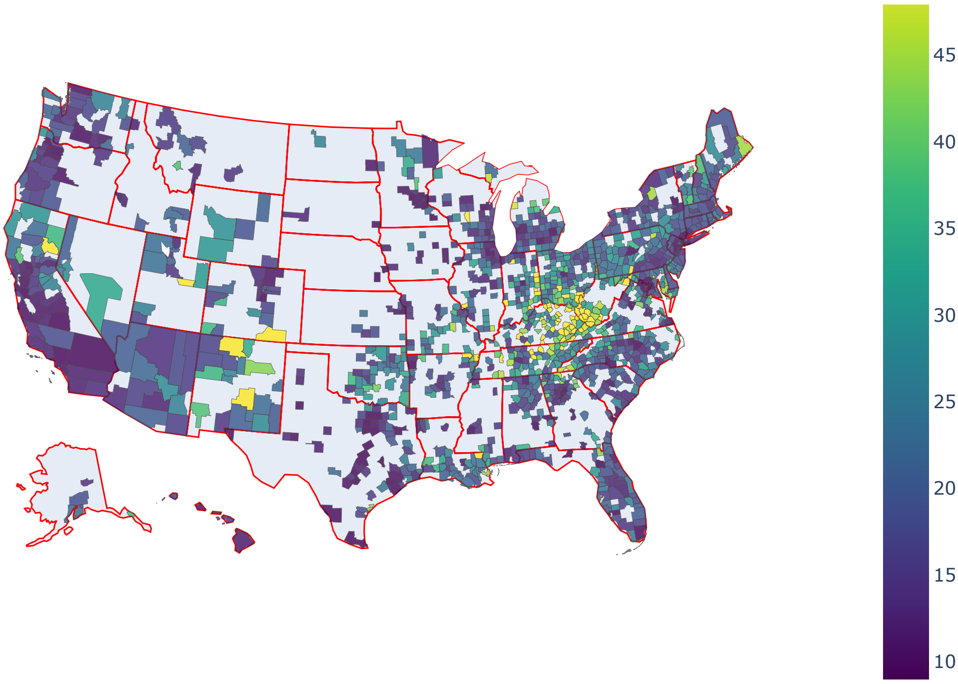

Figure 1: Drug Overdose Death Rate across the United States This figure illustrates the distribution of mean drug overdose rate (per 100,000 people) for the U.S. counties for year 1999-2020. Data is from Center for Disease and Control (CDC), and only published for the counties with at least 10 deaths in a given year. This figure also shows the sample of the counties are covered in the main analysis (i.e., all the tests are conducted at the intensiv margin).

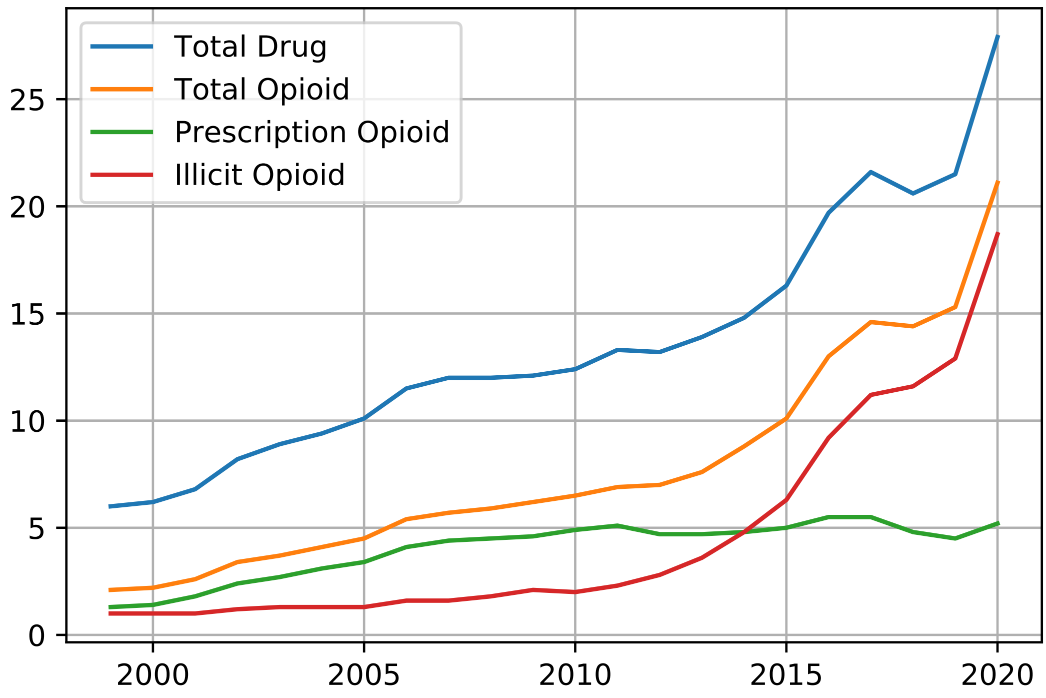

Figure 2: National Opioid Drug Overdose Death Rate. Figure illustrates the national trend of all drug and opioid drug overdose death rates for years 1999-2020. Data is from Center for Disease and Control (CDC).

	N	Mean	SD	P25	P50	P75
Opioid Epidemic						
Total Drug Overdose Deaths	680,125	15.56	9.42	9.54	13.22	18.78
Opioid Overdose Deaths	593,034	10.37	8.50	5.19	8.08	12.71
Prescription Opioid Overdose Deaths	516,671	5.52	4.49	2.67	4.44	7.00
Illicit Opioid Overdose Deaths	431,613	6.42	7.81	1.93	3.63	7.59
Oxycodone Rate 2006-2009	680,125	11.45	7.66	4.84	10.49	16.49
Mortgage Market						
		Fannie Mae+Freddie Mac + HMDA				
60+ days Delinquency Rate, %	646,007	3.51	3.82	0.00	2.25	5.89
90+ days Delinquency Rate, %	644,796	2.53	3.18	0.00	1.11	4.26
90+ days delinquency Rate with CLTV$<$60, %	637,016	0.75	1.55	0.00	0.00	0.69
90+ days Delinquency Rate with CLTV$\geq$60, %	633,082	3.39	4.51	0.00	0.91	6.00
90+ days Delinquency Rate with CLTV$\geq$80, %	575,717	4.39	6.80	0.00	0.00	8.04
Credit Score	546,768	744.28	22.04	730.20	748.25	761.00
Interest Rate, %	551,720	4.74	1.01	3.87	4.34	5.79
Debt-to-Income, %	545,010	33.71	3.85	31.00	33.60	36.31
Loan-to-Value, %	543,018	70.01	7.91	64.56	70.65	76.00
Applicant's Income (1000s)	536,290	84.92	27.64	63.58	81.10	102.77
Loan Amount (1000s)	538,507	183.86	71.09	127.06	173.85	233.02
White Rate	560,600	0.89	0.16	0.85	0.96	1.00
Male Rate	569,159	0.70	0.17	0.59	0.71	0.82
		HMDA				
Mortgage Approval Rate, %	573,865	45.62	8.64	39.62	46.36	52.08
Home Purchase Mortgage Approval Rate, %	573,936	50.15	9.32	43.96	50.65	57.02
Refinancing Mortgage Approval Rate, %	571,788	42.37	10.00	35.11	42.86	50.00
Other Local Indicators						
Population (1000s)	621,800	4.38	2.00	2.98	4.15	5.49
Housing Units (1000s)	620,503	1.79	1.50	1.16	1.63	2.21
House Price Growth (FHFA), %	215,763	3.10	9.39	-2.42	2.88	8.74
House Price Growth (Zillow), %	456,662	2.72	8.04	-1.72	2.90	7.29
Cancer Mortality	680,125	187.01	45.85	152.18	183.19	215.20

Table 1: Summary Statistics. This table reports summmary statistics for the variables used in the main analysis. The sample coverage is for years 2004-2017, and it is restricted to the counties with non-missing $Total\ OD$ data points (i.e., CDC publishes numbers only if the death toll are more than nine).

Panel A: First Stage				
	Opioid OD	Total OD	Opioid OD	Total OD
Oxy Reform x Pre Oxy Supply	0.095***	0.108***	0.095***	0.109***
	(3.12)	(3.88)	(3.04)	(3.93)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	306,541	362,264	305,070	360,579
F-stat.	9.13	15.03	9.24	15.41
Panel B: Second Stage				
	Delinquency rate			
	60+ days		90+ days	
$\widehat{\text{Opioid OD}}$	0.045***		0.041***	
	(2.92)		(2.95)	
$\widehat{\text{Total OD}}$		0.040***		0.036***
		(3.32)		(3.36)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	306,541	362,264	305,070	360,579

Table 2: The Impact of Opioid Epidemic on Mortgage Defaults. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017. *Oxy Reform* is an instrumental variable captures the OxyContin shock to opioid drug supply, that equals to one for years 2011-2017, and zero for 2004-2010 period. *Pre Oxy Supply* measures pre OxyContin reformulation oxycodone exposure, measured as average per capita dosage units of oxycodone supplied by retail and chain pharmacies in county j for 2006-2009 period. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year t respectively. *Delinquency rate* measures mortgage default, computed as the share of 60+, and 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: First Stage				
	Prescription OD	Illicit OD	Prescription OD	Illicit OD
Oxy Reform x Pre Oxy Supply	0.047	0.102***	0.047	0.103***
	(1.43)	(3.04)	(1.41)	(3.08)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	260,071	236,778	258,767	235,662
F-stat	2.04	9.25	1.99	9.46
Panel B: Second Stage				
	Delinquency rate			
	60+ days		90+ days	
$\widehat{\text{Prescription OD}}$	0.086		0.082	
	(1.41)		(1.39)	
$\widehat{\text{Illicit OD}}$		0.040***		0.036***
		(2.94)		(2.98)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	260,071	236,778	258,767	235,662

Table 3: The Impact of Opioid Epidemic on Mortgage Defaults: Placebo test. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 and provides placebo test on the validity of the instrumental variable. *Oxy Reform* is an instrumental variable captures the OxyContin shock to opioid drug supply, that equals to one for years 2011-2017, and zero for 2004-2010 period. *Pre Oxy Supply* measures pre OxyContin reformulation oxycodone exposure, measured as average per capita dosage units of oxycodone supplied by retail and chain pharmacies in county j for 2006-2009 period. *Prescription OD* and *Illicit OD* are proxies for local opioid epidemic, computed as the number of prescription opioid and illicit opioid drug related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 60+, and 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	90+ delinquency rate					
	Manufacture		Poverty		Subprime	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{\text{Opioid OD}}$	0.028**	0.058*	0.020	0.063**	0.030	0.064*
	(2.53)	(1.79)	(1.27)	(2.54)	(1.40)	(1.90)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	154,751	138,384	130,675	174,395	134,414	170,656

Table 4: The Impact of Opioid Epidemic on Mortgage Defaults: Ruling out Economic Despair. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the historical (2001-2005) economic despair rate using mean manufacturing employment, poverty and subprime population rates in six sub-samples: counties with below (*Low*) and above (*High*) median values for each of these variables. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	90+ days delinquency rate			
	Low Insured		High Insured	
Opioid OD	0.199		0.044***	
	(0.51)		(2.70)	
Total OD		0.076		0.041***
		(1.08)		(3.45)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	139,311	164,300	165,728	196,246

Table 5: The Impact of Opioid Epidemic on Mortgage Defaults: Access to prescription opioids. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the 2006 healthcare insurance rate levels in two sub-samples: counties with below (*Low*) and above (*High*) median insurance rate. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	90+ days delinquency rate			
	Low Labor Supply Growth		High Labor Supply Growth	
	(1)	(2)	(3)	(4)
$\widehat{\text{Opioid OD}}$	0.020**		0.100	
	(2.53)		(1.44)	
$\widehat{\text{Total OD}}$		0.020***		0.068**
		(3.13)		(2.06)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	149,607	176,740	155,338	183,703

Table 6: The Impact of Opioid Epidemic on Mortgage Defaults: The Role of Labor Supply Growth - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the labor supply growth levels in two sub-samples: counties with below (*Low*) and above (*High*) median annual labor supply growth at year t. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	90+ days delinquency rate			
	Low Income Growth		High Income Growth	
	(1)	(2)	(3)	(4)
$\widehat{\text{Opioid OD}}$	0.026***		0.075*	
	(2.98)		(1.66)	
$\widehat{\text{Total OD}}$		0.029***		0.046***
		(2.77)		(2.85)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	154,467	181,664	150,289	178,595

Table 7: The Impact of Opioid Epidemic on Mortgage Defaults: The Role of Income Growth - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the income growth levels in two sub-samples: counties with below (*Low*) and above (*High*) median annual income growth at year t. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	House Price Growth			
	Zillow	FHFA	Zillow	FHFA
	(1)	(2)	(3)	(4)
$\widehat{\text{Opioid OD}}$	-8.780**	-8.605**	-7.787**	-8.155**
	(-2.17)	(-2.37)	(-2.07)	(-2.26)
90+ days delinquency rate			-0.796***	-0.721***
			(-6.96)	(-6.72)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	140,489	164,615	140,489	164,615

Table 8: Opioid epidemic and house price growth - Second stage estimates. This table reports estimates of how opioid epidemic relates to house price growth for years 2004-2017. *Opioids OD* is a proxy for local opioid epidemic, computed as the number of opioid drugs related overdose deaths per 100,000 residents for a county j at year $t-1$. Tract-level annual house price growth measures (in percent) are obtained from two different sources: Zillow and Federal Housing Finance Agency (FHFA). As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	90+ days delinquency rate					
	CLTV $<$ 60		CLTV$\geq$60		CLTV$\geq$80	
$\widehat{\text{Opioid OD}}$	0.008**		0.059***		0.103***	
	(2.40)		(3.03)		(2.68)	
$\widehat{\text{Total OD}}$		0.008***		0.052***		0.088***
		(2.97)		(3.47)		(3.20)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	303,329	358,175	304,398	360,116	291,761	346,281

Table 9: Opioid epidemic and mortgage default: Current loan balance to current house value (CLTV) - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the level of CLTV. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local enviroment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	Loan approval rate					
	All		Home Purchase		Refinance	
	(1)	(2)	(3)	(4)	(5)	(6)
Opioid OD	-0.045**		-0.091***		-0.059**	
	(-2.51)		(-3.73)		(-2.31)	
Total OD		-0.037***		-0.070***		-0.050***
		(-3.00)		(-4.62)		(-2.76)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	280,624	329,402	280,996	329,629	280,697	330,343

Table 10: Opioid epidemic and mortgage origination - Second stage estimates. This table reports estimates of how opioid epidemic has affected lenders' decisions on mortgage applications for years 2004-2017. *Mortgage approval rate* measures accepted loan application rate by lenders, computed as the number of applications approved for all, home purchase and refinancing mortgages divided by total number of all, home purchase and refinancing mortgage applications received in census tract i at year t. *Opioid OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. Census tract-level credit environment controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, which are constructed based on originated loan samples. Application based census-tract level controls include *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local socioeconomic controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

A Appendix

A.1 Additional Tables and Figures

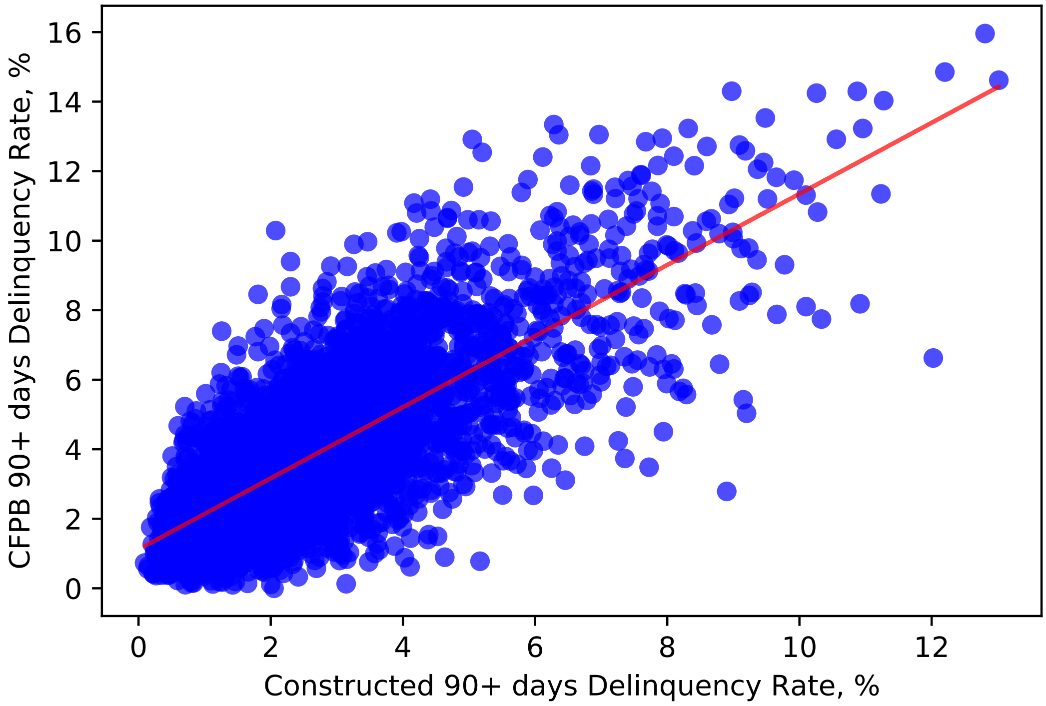

Figure A1: Constructed Delinqeuncy Rate vs CFPB Delinquency Rate for 2008-17: ***corr = 0.76*****.** This figure illustrates the correlation between constructed delinquency rate using Fannie Mae, Freddie Mac and HMDA datasets and county level delinquency rate data by Consumer Finance Protection Beaure (CFPB) for years 2008-17. CFPB started publishing data from 2008, and it is available for the counties with at least 1,000 mortgages outstanding (471 counties out of 3006) https://www.consumerfinance.gov/data-research/mortgage-performance-trends/download-the-data/.

	Delinquency rate			
	60+ days		90+ days	
$\widehat{\text{Opioid OD}}$	0.045**		0.041***	
	(2.58)		(2.60)	
$\widehat{\text{Total OD}}$		0.040***		0.035***
		(3.06)		(3.09)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	222,893	261,466	221,775	260,150

Table A1: The Impact of Opioid Epidemic on Mortgage Defaults: Excluding Financial Crisis Period - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 excluding 2008-2011 period. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 60+, and 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	90+ days delinquency rate			
Opioid OD	0.030***	0.029***		
	(2.74)	(2.75)		
Total OD			0.026***	0.025***
			(3.12)	(3.13)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	No
Cohort x Year FE	No	Yes	No	Yes
Obs.	2057629	2057629	2381595	2381595

Table A2: The Impact of Opioid Epidemic on Mortgage Defaults: Cohort and Year Fixed Effects - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 period for the sample with loan cohort dimension. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drug and all drug related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of loan origination period census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local socio-economic controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Delinquency rate			
	60+ days		90+ days	
$\widehat{\text{Opioid OD}}$	0.055***		0.050***	
	(2.65)		(2.67)	
$\widehat{\text{Total OD}}$		0.049***		0.044***
		(3.00)		(3.04)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	288,968	336,675	287,538	335,059

Table A3: The Impact of Opioid Epidemic on Mortgage Defaults: Excluding Appalachian Counties - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 excluding Appalachian counties. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 60+, and 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Delinquency rate			
	60+ days		90+ days	
$\widehat{\text{Opioid OD}}$	0.032***		0.028***	
	(3.88)		(3.91)	
$\widehat{\text{Total OD}}$		0.030***		0.026***
		(4.27)		(4.29)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	285,434	339,989	284,353	338,712

Table A4: The Impact of Opioid Epidemic on Mortgage Defaults: Excluding Florida - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 excluding Florida. *Opioids OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 60+, and 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

	Default			
	120+ days delinquency rate		Foreclosure Rate	
$\widehat{\text{Opioid OD}}$	0.036***		0.007**	
	(2.93)		(2.11)	
$\widehat{\text{Total OD}}$		0.032***		0.006**
		(3.37)		(2.27)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	304,198	359,586	302,115	356,943

Table A5: The Impact of Opioid Epidemic on Mortgage Defaults: Alternative Default Measures - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 using alternative mortgage default measures. *Opioid OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *120+ days delinquency rate* and *Foreclosure rate* measure mortgage default, computed as the share of 120+ days delinquent and foreclosed mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	90+ days delinquency rate			
	Negative Labor Supply Growth		Positive Labor Supply Growth	
	(1)	(2)	(3)	(4)
$\widehat{\text{Opioid OD}}$	0.037		0.038***	
	(1.02)		(3.01)	
$\widehat{\text{Total OD}}$		0.029		0.034***
		(1.29)		(3.49)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	89,204	109,488	215,741	250,952

Table A6: The Impact of Opioid Epidemic on Mortgage Defaults: Robustness to the Role of Labor Supply Growth - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the labor supply growth levels in two sub-samples: counties with negative and positive annual labor supply growth at year t. *Opioid OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Sample	90+ days delinquency rate			
	Negative Income Growth		Positive Income Growth	
	(1)	(2)	(3)	(4)
$\widehat{\text{Opioid OD}}$	0.013		0.042***	
	(0.57)		(3.06)	
$\widehat{\text{Total OD}}$		0.030		0.034***
		(1.02)		(3.59)
Controls	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	61,794	72,972	242,958	287,287

Table A7: The Impact of Opioid Epidemic on Mortgage Defaults: Robustness to the Role of Income Growth - Second stage estimates. This table reports estimates of how opioid epidemic relates to households defaults on mortgages for years 2004-2017 depending on the income growth levels in two sub-samples: counties with negative and positive annual income growth at year t. *Opioid OD* and *Total OD* are proxies for local opioid epidemic, computed as the number of opioid drugs and all drugs related overdose deaths per 100,000 residents for a county j at year $t-1$ respectively. *Delinquency rate* measures mortgage default, computed as the share of 90+ days delinquent mortgages among all outstanding mortgages for a census tract i at year t. As of origination census tract-level loan controls include *Interest Rate*, *Loan-to-Value Ratio*, *Debt-to-Income Ratio*, *Credit Score*, *Log(Applicant Income)*, *Log(Loan Amount)*, *White Applicant Rate*, and *Male Applicant Rate* . Local environment controls include *Log(Population)*, *Log(Housing Units)*, *Hospital Rate* and *Cancer Mortality Rate*. All controls are normalized to standard deviation of one and mean zero, lagged by one year and parameter estimates are obtained by 2SLS specified in Equation 1. All regressions include controls and fixed effects indicated in the table, whose coefficients I do not report. t-statistics, based on standard errors clustered by county, are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.