Opioid Crisis and Local Economic Pain: Evidence from Commercial Real Estate Loan

Yildiray Yildirim*

Jian Zhang[†] Bing Zhu[‡]

Abstract

This study examines the local economic impacts of the opioid epidemic by focusing on the performance of commercial real estate loans. Using exogenous variations in primary physicians per capita and state-level Opioid Misuse Prevention Legislation, we find that opioid abuse reduces net operating income and increases vacancy rates, leading to higher loan defaults. The disruption in local economies is driven by reduced business sales and decreased neighborhood desirability. The effects are more pronounced in residential and retail properties, areas with weaker economic conditions, communities with minority and young populations, and Republican states.

JEL Codes: R3, G01, G28, D10, D12

Keywords: Opioid Epidemic, Commercial Mortgage, Economic Impacts, Loan Defaults

*Yildiray Yildirim is at the Baruch College. Email:: yildiray.yildirim@baruch.cuny.edu

[†]Jian Zhang is at the Hong Kong University Email: zhangj1@hku.hk

[‡]Bing Zhu is at Technical University of Munich Email: b.zhu@tum.de

We benefited from the comments of seminar and conference participants at Baruch College, Virginia Tech, Boğaziçi University, University of Hong Kong, and 2024 AREUEA International.

1 Introduction

The opioid epidemic has become one of the most severe public health crises in the United States, with far-reaching economic and social consequences. Since the early 2000s, the widespread misuse of prescription opioids has contributed to an unprecedented increase in addiction rates, overdose deaths, and associated healthcare costs. In 2021, more than 500,000 people had died from opioid overdoses, and many more continue to suffer the long-term consequences of addiction and related diseases¹. The opioid crisis not only imposes direct healthcare costs, such as emergency services and long-term addiction treatment, but also affects labor markets, public finance, and local economies. The total economic cost of the opioid crisis in 2018 is estimated to exceed \$696 billion, or roughly 3.4% of US GDP (Council of Economic Advisers, 2019). Despite these staggering figures, the full scope of its impact on financial markets, particularly commercial real estate (CRE), has not been thoroughly examined.

Previous research has primarily focused on the public health dimensions of the opioid crisis, examining its effects on mortality, addiction rates, and healthcare utilization (Hadland et al., 2019). Recent studies have begun investigating its impacts on the labor market, with findings suggesting that opioid addiction reduces labor force participation and increases unemployment, particularly in regions already suffering from economic hardship (Krueger, 2017; Aliprantis and Fee, 2019; Harris, Kessler and Murray, 2021). Beyond these labor market effects, broader research has explored the ripple effects of systemic and localized shocks on financial markets, including how such disruptions propagate through real estate and credit systems (e.g., Gupta et al. (2022)). Understanding these impacts extends beyond economics into crucial sociopolitical territory. For example, a recent article in The New Yorker reveals how the opioid epidemic may have shaped political dynamics, with fentanyl-affected communities potentially playing a decisive role in the political landscape, including

¹https://www.cdc.gov/opioids/basics/epidemic.html

potentially fueling Donald Trump's return to the White House².

The economic disruption of opioid misuse extends beyond labor markets and spills over into consumer spending, as households grappling with opioid addiction often experience significant financial strain. Lower disposable income among addicted individuals and their families leads to reduced local consumption, particularly in the retail sectors dependent on consistent demand. As a result, local businesses in opioid-affected areas, especially those in the retail and service sectors, suffer from declining sales and are more likely to downsize or close. The combined effects of reduced business activity and weakened consumer spending ripple through the commercial real estate sector, increasing financial pressure on property owners and investors. Lower net operating income (NOI) and higher vacancy rates make it difficult for property owners to service their debt, leading to higher default rates on commercial real estate loans. Retail and multifamily properties are particularly vulnerable, as they are more directly affected by shifts in local demand and tenant financial stability.

This paper adds to the literature by focusing on how opioid misuse affects the performance of commercial real estate loans, an area that has received limited attention despite the importance of the CRE sector for local economies. We hypothesize that increased opioid misuse leads to higher mortgage delinquency rates from CRE through two main channels: (1) reduced financial stability of households and businesses, resulting in lower net operating incomes and higher vacancy rates for commercial properties; and (2) a greater economic slowdown, particularly in the retail and multifamily housing sectors, leading to increased risk of loan default. Despite the importance of the CRE sector for local economies, this area has received limited attention.

The commercial real estate market, which includes sectors such as retail, office, and multifamily housing, is a critical component of economic infrastructure. It supports business operations, provides housing, and contributes to local tax revenues. The financial health of this sector is closely tied to local economic conditions, with factors such as consumer de-

²https://www.newyorker.com/news/the-lede/did-the-opioid-epidemic-fuel-donald-trumps-return-to-the-white-house

mand, business activity, and labor market performance directly influencing property values, occupancy rates, and the risk of default on loans. By exploring the relationship between opioid misuse and CRE loan performance, this paper sheds light on a novel economic spillover effect of the opioid crisis—its impact on local real estate markets and financial stability.

Our analysis draws on a rich dataset of commercial real estate loans from the Commercial Mortgage-Backed Securities (CMBS) market, which covers a large proportion of CRE loans in the U.S. over the period from 2011 to 2019(Griffin and Priest, 2023). Notably, this time frame overlaps with what is often termed the "second wave" of the opioid crisis, during which prescription practices and public policies were in flux, making it especially relevant for analyzing the financial consequences of opioid misuse. This data set includes detailed information on loan performance, property characteristics, and local economic conditions, allowing us to examine the impact of opioid abuse at a granular level. By merging these data with opioid distribution data from the Drug Enforcement Administration (DEA) and economic indicators from the Bureau of Labor Statistics (BLS), we are able to capture both the direct and indirect effects of opioid misuse on loan outcomes.

We find that the probability of default for local CRE mortgages increases with local distribution of opioid pills. Specifically, a one standard deviation increase in opioid pill distribution per capita in the zipcode where the property is located is associated with a 0.42% increase in over 60-day delinquency. Given the average annual 60-day delinquency rate of 0.28%, our results imply an increase of nearly twofold. The coefficient of interest remains robust even after accounting for dynamic and static mortgage attributes, property characteristics, local economic conditions, and alternative definitions of CRE mortgage delinquency based on 30 and 90 days instead.

To establish a causal relationship between opioid abuse and CRE loan performance, we employ an instrumental variable (IV) approach that takes advantage of exogenous variation in opioid distribution. Specifically, we use payments from opioid-related pharmaceutical companies to physicians as an instrument for local opioid prescription rates. Previous research has shown that pharmaceutical payments are a key driver of opioid prescribing patterns, with higher payments leading to greater opioid distribution (Hadland et al., 2019; Fernandez and Zejcirovic, 2018). These payments are exogenous to local economic conditions, as they reflect the marketing strategies of pharmaceutical companies rather than the demand for opioids within a given region. This allows us to isolate the impact of opioid abuse on loan performance from other unobserved factors that could affect local real estate markets. We provide consistent evidence that the increase in the opioid epidemic has a significant positive impact on CRE mortgage delinquency rates. This impact is also economically meaningful and similar to the baseline estimate.

Moreover, we conduct a series of robustness checks on the measurements for the distribution of opioid pills. First, to accommodate various dosages, we standardize the strength of opioids using the MME value for each pill and calculate the yearly distribution of milligram equivalents of morphine (MME) per ZIP code. Secondly, we use lagged opioid pill distribution to allow a time lag between opioid prescription and the spillover effect. Third, rather than solely relying on the ZIP code, we calculate the pills shipped to pharmacies within 1 km and 3 km radii of the property. Lastly, we focus on the distribution channel of these pills, using the pills sold through pharmacies with the least oversight as the instrument. All approaches consistently show economically and statistically significant increases in the default probability of local CRE loans.

In addition to our IV approach, we take advantage of the staggered adoption of statelevel prescription drug monitoring programs (PDMP) to evaluate the effectiveness of regulatory interventions in mitigating the financial consequences of the opioid crisis. PDMPs are designed to monitor and control the distribution of prescription opioids, reducing the risk of abuse and addiction. Using a difference-in-differences (DiD) methodology, we compare the performance of CRE loans in states that implemented PDMPs with those that did not, before and after the adoption of these programs. This natural experiment allows us to assess whether public health interventions can alleviate the economic and financial damage caused by opioid abuse, providing valuable insights for policymakers seeking to mitigate the broader impact of the crisis.

We conduct two robustness checks on DiD estimates and the inference remains unchanged. First, to mitigate the unobserved factors that influence both opioid abuse and CRE loan performance across states, we also create a matched sample of states with and without opioid-limiting laws based on our state-level economic and demographic condition. A two-way fixed effects (TWFE) estimator may yield biased estimates when there is heterogeneity in the treatment effects within units over time or between groups of units treated at different times, even if the parallel trend assumption holds (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). So we adopt the estimation routine proposed by Callaway and Sant'Anna (2021) to avoid the pitfalls that arise in the presence of heterogeneous or dynamic treatment effects.

Next, we present several pieces of evidence to support the economic channels through which the opioid epidemic can negatively impact the performance of Commercial Real Estate (CRE) loans. We first show that areas with higher potential for opioid abuse often experience a decrease in net operating income (NOI) and occupancy rates, subsequently increasing the default risk of CRE mortgages. Using the Alex database and the National Neighborhood Data Archive, we also present direct evidence of how opioid misuse disrupts local economies. Increased opioid use negatively affects local business sales and erodes neighborhood desirability, which in turn reduces net operating income (NOI) and occupancy rates of local properties.

We further explore the cross-sectional effects of opioid distribution on mortgage delinquency across different property types and local economic conditions. Consistent with the idea that prolonged opioid use can decrease family spending or create difficulties in paying rent, our findings show that the correlation between mortgage delinquency and the distribution of opioid pills originates primarily from residential and retail buildings. The effect also varies with local economic conditions, as areas with lower health insurance coverage, fewer job opportunities, and higher rental costs as a percentage of income experience a stronger adverse impact from opioid abuse. Last, we show that communities with higher proportions of Black and Asian populations or younger individuals, and those in Republican states, are more severely affected by opioid abuse.

In our final set of analyses, we adopt a holistic approach to assess the implications of asset pricing in opioid epidemics. In zipcodes with high opioid pill concentrations, lenders' inability to identify tenants at risk of opioid abuse can increase credit risks, leading to higher borrowing costs and more stringent lending criteria. We find that a one standard deviation increase in opioid distribution is associated with a 23 pbs increase in the initial spread of CRE loans, a 2.7% decrease in the initial TLV, and a 77.2% increase in the debt service coverage ratio, backed by local properties. These factors limit borrowers' access to credit and increase investors' borrowing costs, highlighting the spillover effects of opioid abuse on the local credit environment and its role in exacerbating economic disparities.

This paper provides the first empirical analysis of the impact of the opioid crisis on commercial real estate loan performance, highlighting a previously overlooked economic spillover effect. By combining insights from health economics, financial markets, and public policy, we show that opioid abuse significantly increases the risk of CRE loan defaults, particularly in economically distressed regions. Furthermore, our findings demonstrate that public health interventions, such as PDMPs, can help mitigate these negative effects, offering important lessons for policymakers seeking to address the broader economic and financial consequences of public health crises. Research contributes to a growing body of literature on the intersection of public health and economic policy, providing actionable insights to manage the long-term economic damage caused by opioid addiction.

The implications of these findings are significant for both policymakers and participants in financial markets. The opioid crisis is not only a public health emergency, but also a major economic disruption that poses risks to local economies and financial markets. Our results highlight the need for coordinated public health and economic policies to address both the human and financial toll of opioid addiction. Public health interventions such as PDMP can help reduce the spread of opioid abuse, but targeted economic policies may also be necessary to support regions hardest hit by the crisis. These policies could include job training programs, economic development incentives, and direct financial assistance to mitigate the impact on local businesses and real estate markets. By addressing both the health and economic dimensions of the opioid crisis, policy makers can reduce long-term economic damage and support the recovery of affected communities.

Our analysis contributes to two key strands of the literature. First, it extends the broad research on health and finance (Parise and Peijnenburg, 2019; Koijen and Van Nieuwerburgh, 2020; Gupta et al., 2022). In particular, we are related to the literature on the economic consequences of the opioid crisis, which has primarily focused on labor market impacts and municipal finance. Past literature provides evidence on the negative impact of opioid misuse on municipal finances, local real estate prices, and individual employment(Cornaggia et al., 2022; Custodio, Cvijanovic and Wiedemann, 2023; Ouimet, Simintzi and Ye, 2023). Our findings focus on the ripple effects of opioid abuse on local economies. In particular, we highlight a specific mechanism that has not been thoroughly explored: how opioid addiction affects commercial real estate markets through loan performance. Second, the results of this analysis also contribute to the broad literature on the drivers of mortgage credit supply and default (Campbell and Cocco, 2015; Bradley, Cutts and Liu, 2015; Agarwal et al., 2015; Gupta and Hansman, 2022; Gao, Yi and Zhang, 2024; Cespedes, Parra and Sialm, 2024). The opioid epidemic represents a localized public health shock with significant financial implications, and our study provides new insights into how such crises can affect commercial real estate markets.

Furthermore, our paper is related to government policy interventions in response to economic crises. For example, the Home Affordable Refinance Program (HARP), created by the federal government to combat the financial crisis in 2007, increased the refinance rate by 1.5%. This led to an aggregate increase in US consumption of approximately \$20

billion (Agarwal et al., 2023). Similarly, Agarwal et al. (2021) demonstrated that the US federal government's Paycheck Protection Program (PPP), aimed at combating the economic consequences of COVID-19, effectively alleviated financial distress for small businesses and reduced mortgage delinquencies by around \$36 billion in 2020. These examples underscore the importance of targeted policy interventions in stabilizing financial markets during crises. Our findings on the financial market consequences, particularly the financing cost and credit access for local CRE loans and pricing implications in the CMBS market³ underscore the need for public health interventions to minimize opioid abuse.

Overall, our results underscore a previously underexplored mechanism by which a public health crisis can generate significant externalities in local financial markets. By demonstrating that opioid misuse not only exacts a human and labor-market toll but also destabilizes commercial property performance, this paper calls attention to the need for integrated public health and economic policies. These findings suggest that regulatory interventions aiming to reduce excessive opioid prescriptions may also help stabilize commercial real estate, especially in more vulnerable communities that rely on consistent tenant demand and consumer spending. In doing so, our work highlights the broader economic stakes of addressing the opioid epidemic and emphasizes how mitigating its human costs can also curb adverse outcomes in local real estate and lending markets.

The remainder of the paper is structured as follows. Section 2 describes the data used in this study, Sections 3 and 4 present the main results along with the analysis of the mechanism. Section6 shows the effect on the pricing of CMBS and Section 7 concludes.

³CMBS is a financial vehicle that pools mortgages collateralized by commercial properties and originated from many lenders into a single trust that is sold to multiple investors. The CMBS market provides an important source of liquidity for lenders, accounting for 23% of the \$3.4 trillion in U.S. nonresidential commercial mortgage debt (Serivice (2020); Fuster, Lucca and Vickery (2023)).

2 Data

Our study employs a unique dataset that combines detailed loan-level information on commercial mortgage-backed securities (CMBS) with opioid prescription data and local economic and demographic characteristics. This integrated data set allows us to examine how regional opioid misuse impacts commercial real estate (CRE) loan performance, with particular attention to loan defaults and delinquency. In the following, we describe the main data sources used in this analysis and the key variables extracted from each.

2.1 CMBS Loans

Our primary source of data on commercial real estate loans is the Trepp database, which is the leading provider of commercial mortgage-backed securities (CMBS) data. Trepp is widely used in the commercial real estate industry and provides a comprehensive view of CMBS transactions, including detailed information on loan performance metrics, property-level characteristics, and deal structures. Nationally, the Trepp dataset includes 106,969 loans, aggregated into approximately 1,200 deals since 1965, representing a total loan volume of approximately USD 1.14 trillion in commercial real estate mortgages (Holtermans, Kahn and Kok, 2022; Agarwal et al., 2024). For the purposes of this study, we focus on CMBS loans issued between January 2011 and December 2018, allowing us to align with the availability of opioid prescription data. However, we track the performance of these loans through December 2019, so that we can capture how loan outcomes evolved over time, particularly during the peak years of the opioid epidemic. This extended period is crucial for observing the long-term financial effects of opioid-related economic distress on commercial real estate markets, especially as the crisis impacted employment, income levels, and tenant stability in affected regions.

Our final sample includes 35,333 loans across 962 deals, covering a wide range of property types, primarily multifamily housing (70%), followed by retail properties (11.3%)

and office buildings (5.4%). Table 1 provides the summary statistics, including key loan characteristics, ZIP code attributes, and opioid prescription rates. These loans have an average interest rate of 4.5%, an average loan-to-value (LTV) ratio of 73.9%, and an average occupancy rate of 93%. The average net operating income (NOI) is USD 1.99 million and the average loan term is 86 months. These characteristics reflect typical commercial real estate lending conditions, with LTV ratios indicating moderate leverage in most loans.

Over time, 0.28% of these loans were reported in 60 or more days of delinquency, foreclosure, or real estate-owned (REO) status, reflecting financial stress in some areas. Loan delinquency serves as a key indicator of the economic viability of properties and the broader health of the commercial real estate market. Furthermore, 17.1% of the loans in our sample show overstatements of net operating income (NOI) by more than 5% at the time of securitization, which may indicate inflated income projections by loan originators. 8.7% of the loans are interest-only loans, which defer principal payments and can exacerbate financial risk for borrowers, especially during periods of economic stress.

The distribution of property construction years is relatively equal over time, with nearly 20% of the properties built between 2000 and 2010, another 20% between 1980 and 1990, and 15% between 1970 and 1980. Older properties may be more susceptible to maintenance costs and vacancy risk, while newer properties often have lower vacancy rates and higher rents, potentially contributing to better loan performance.

The properties in our sample are located in ZIP codes with diverse economic and demographic characteristics. On average, these ZIP codes report a total employment of 18,019⁴, an average Herfindahl index for business concentration of 16.4%, and an average monthly rent price of USD 901. These figures highlight economic diversity between regions, with some ZIP codes showing greater resilience due to diversified local economies, while others are more dependent on specific industries that may be vulnerable to opioid-related

⁴The employment data is from the Zip Code Business Patterns (ZCBP) database for local job distributions. Although the ZCBP database reports employment by the NAICS sector, it provides the number of establishments at the ZIP code level, not the exact employment count. We impute total employment using the median number of employees in each size category and multiplying it by the number of establishments in each group.

economic shocks.

In ZIP codes with higher opioid distribution rates, economic stress tends to be more pronounced. These areas often experience reduced economic productivity and higher healthcare costs due to the pervasive effects of opioid addiction on local labor markets. The economic stress on households in these regions can reduce consumer spending, particularly in the retail and multifamily housing sectors, leading to lower occupancy rates and decreased NOI, which in turn increases the likelihood of loan delinquency. These areas are also likely to experience greater instability in commercial real estate performance as property owners struggle to maintain rental income and meet their debt obligations amid declining local economic conditions.

In addition, many of the properties in the data set are located in ZIP codes with significant uninsured populations. On average, 14.9% of the population in these areas lacks access to private or public health insurance, which further exacerbates financial vulnerability. The lack of healthcare coverage is particularly acute in regions affected by the opioid crisis, as it increases out-of-pocket healthcare costs for affected households, reducing disposable income and increasing the risk of default for both tenants and property owners.

In terms of demographic composition, 20.1% of the population in these ZIP codes is over the age of 60, and 57.3% of the population is between 20 and 60 years old, the prime working age group. The male-to-female ratio is approximately 0.97, and 12.0% of the population are disabled. Additionally, 7.3% of the population works fewer than 17 weeks per year, indicating a significant degree of economic instability. In ZIP codes with high levels of economic instability—particularly those with high unemployment or low income levels—the effects of the opioid crisis are likely to compound financial stress. Properties located in these regions are more vulnerable to declining property values and falling rental income, both of which contribute to higher loan default rates and increased financial instability in the commercial real estate market.

[Place Table 1 about here]

2.2 **Opioid Prescription Data**

We utilize data from the Automation of Reports and Consolidated Orders System (ARCOS), managed by the Drug Enforcement Administration (DEA), to measure opioid distribution at the ZIP code level. ARCOS tracks the distribution of controlled substances, including opioids such as oxycodone and hydrocodone, which are among the most widely prescribed and misused opioids in the US. The data set covers 760 million transactions across 16,075 ZIP codes from 2011 to 2019, providing a comprehensive view of opioid distribution patterns and their economic impacts on local real estate markets (Custodio, Cvijanovic and Wiedemann (2023)).

For each ZIP code, we calculate the intensity of opioids, defined as the number of opioid pills distributed per capita. The average opioid intensity in ZIP codes is 40 opioid pills per person, with significant variation observed across regions. Some areas, particularly in the Midwest and Southeast, show markedly higher concentrations of opioid distribution. ZIP codes without opioid transaction data are excluded from the sample. This measure of opioid intensity allows us to examine the localized effects of opioid misuse and its potential economic consequences, especially in relation to commercial real estate (Currie, Jin and Schnell (2019)).

Figure 1 illustrates trends in opioid prescriptions and pharmaceutical payments to physicians over time. The gray dashed line shows a consistent decline in opioid prescriptions per capita from 2011 to 2019, reflecting the impact of regulatory measures and public health initiatives Fernandez and Zejcirovic (2018). In contrast, the solid black line represents pharmaceutical payments to physicians, which fluctuated during the same period, peaking in 2014 and 2018. These payments, which incentivized opioid prescriptions, contributed significantly to the opioid crisis in regions with higher opioid distribution rates, even as prescription rates began to decline (Hadland et al., 2019).

To further refine our analysis, we incorporate data from the Centers for Medicare & Medicaid Services (CMS) Open Payments database, which tracks pharmaceutical payments to physicians. These payments reflect financial incentives provided by opioid manufacturers to healthcare providers to promote opioid medications. The geographic distribution of these payments mirrors the regions hardest hit by opioid misuse, revealing that both ZIP codes and counties with higher payments also tend to have higher opioid prescription rates ((Hadland et al., 2019)). By including these data, we can assess the broader economic implications of these financial incentives and their subsequent impact on local real estate markets.

Figure 2 provides a comprehensive view of opioid-related activity at the ZIP code and county levels. Figure 2a maps the distribution of opioid pills at the ZIP code level, identifying the Midwest and Southeast as the regions with the highest concentrations of opioid distribution (Ouimet, Simintzi and Ye (2023)). In contrast, Figure 2b illustrates the distribution of opioid pills at the county level, offering a broader perspective of how the opioid crisis has spread regionally. The localized impact is further analyzed in Figure 2c, which shows pharmaceutical payments to physicians at the ZIP code level, indicating that ZIP codes with higher opioid intensity also tended to receive larger pharmaceutical payments (Aliprantis and Fee (2019)). Meanwhile, Figure 2d maps pharmaceutical payments at the county level, revealing a similar trend on a broader geographic scale, with higher payments in counties that also reported higher opioid prescription rates (Krueger (2017)).

These figures highlight the connection between high opioid intensity and economic distress in specific regions. ZIP codes with increased opioid intensity and higher pharmaceutical payments are more likely to experience a decline in local economic activity, leading to reduced net operating income (NOI) and lower occupancy rates in both multifamily housing and retail properties. The reduction in property income exacerbates financial distress and contributes to higher delinquency and default rates on commercial real estate loans.

[Place Figure 1 about here]

[Place Figure 2 about here]

Figure 3 illustrates the passage of opioid-limiting laws across the United States, high-

lighting when states implemented regulations to limit opioid prescriptions. These laws, enacted primarily between 2016 and 2018, set restrictions on the duration and dosage of opioid prescriptions and require physicians to consult Prescription Drug Monitoring Programs (PDMPs) before issuing prescriptions. States that adopted these regulations earlier, such as Massachusetts and New York, saw more rapid declines in opioid prescriptions, which corresponded to improved mortgage delinquency rates. This suggests that regulatory interventions aimed at curbing opioid misuse can also alleviate some of the broader financial strains caused by the opioid crisis.

By integrating ARCOS data on opioid distribution, pharmaceutical payments, and opioid-limiting laws with ZIP code- and county-level loan performance data, we provide a comprehensive analysis of how the opioid epidemic has contributed to financial stress in local economies. ZIP codes with higher opioid intensity are more likely to experience higher loan delinquency rates, particularly in multifamily housing and retail property sectors, which are more sensitive to local economic disruptions. Additionally, regions with larger uninsured populations and higher economic instability are more likely to experience heightened financial stress, leading to increased loan defaults and contributing to financial instability in commercial real estate markets.

[Place Figure 3 about here]

2.3 Local Economic Activities

To capture the impact on local economic performance, we utilize the Data Axle database for establishment-level information, which is comparable to the NETS Publicly Listed Database from Wall & Associates (Reid and Sobczak, 2022). Importantly, the database provides details on a company's yearly revenue generated at each establishment site. This enables us to track local sales across locations over time and assess the economic consequences of the opioid crisis. Our analysis focuses on the retail sector. We also supplement the analysis using the

National Neighborhood Data Archive (NaNDA) to evaluate the impact on neighborhood characteristics (Khan et al., 2024; Pearson et al., 2023). NaNDA, a publicly accessible repository, provides data on the number of establishments across various amenity categories at both census tract and zip code levels using the data source of NETS (Melendez and Dyke, 2024).

3 Opioid Abuse and CRE Mortgage Performance

In this section, we estimate the relationship between opioid abuse and mortgage delinquency using an instrumental variable (IV) approach. We also assess the robustness of our findings by considering alternative measures of opioid abuse, different definitions of mortgage delinquency, and lagged effects. Lastly, we conduct a difference-in-differences (DiD) analysis to evaluate the impact of opioid-limiting laws on mortgage performance.

3.1 **Baseline Estimation**

To quantify the impact of opioid abuse on commercial mortgage delinquency, we utilize a dataset consisting of 1,630,069 loan-month observations on detailed loan performance metrics across time and geographic regions and estimate the following specification:

$$Y_{i,j,t} = \alpha OP_{i,t} + \delta X_{i,t} + \tau_t + \omega_j + \upsilon_{i,j,t}.$$
(1)

where $Y_{i,j,t}$ represents the indicator variable that equals one if the loan *i* originated in state *j* is delinquent for over 60 days at month *t*. Our primary independent variable, $OP_{i,t}$, measures the number of opioid pills distributed per capita (scaled by 100) in the ZIP code where the property is located. A comprehensive set of control variables, $X_{i,t}$, accounts for dynamic and static factors related to mortgage attributes, property characteristics, and local economic performance. This model includes time fixed effects, τ_t , to account for macroeconomic fluctuations and regional shocks, and state fixed effects, ω_j , to control for time-invariant factors specific to local economy. The error term, $v_{i,j,t}$, captures unobserved factors affecting loan delinquency.

To account for local economic conditions, we include the total number of employments, business concentration measured by the Herfindahl index of employments across three digital industry sectors, age 20-60 ratio, age over 60 ratio, male population to female ratio, disability rates, the proportion of individuals lacking public or private health insurance coverage, poverty rates, unemployment rates, median rental costs and total number of physicians in the zipcode. This choice is informed by prior research indicating the significant impact of local economic factors on commercial real estate performance ((Fisher et al., 2022; Liu, Zheng and Zhu, 2022)). Furthermore, we control for loan-specific characteristics, comprising loan-to-value ratios, loan rates, loan durations, a dummy varaible for income overstatements at securitization ⁵ and the prevalence of interest-only loans. These loan-level metrics are computed over the duration of the securitization period. Consistent with the methodology outlined by Eichholtz, Steiner and Yönder (2019) we incorporate vintage shares based on the year of construction, recognizing that the age distribution of buildings can vary across cities, with some, like New York, characterized by older structures compared to rapidly expanding urban centers. Vintage categories are delineated as follows: before 1960, between 1960 and 1970, between 1970 and 1980, between 1980 and 1990, between 1990 and 2000, between 2000 and 2010, and after 2010. Additionally, we include other pertinent factors such as the composition of property types, indicator variables for deal types (e.g., Agency CMBS, Agency Pools, Conduit, Miscellaneous, Single Assets), state-specific dummies, and dummies for securitization year-months.

The results, as presented in Table 2, Column 1, provide a baseline estimate of the direct relationship between opioid distribution and mortgage delinquency without using

⁵Griffin and Priest (2023) demonstrate that the property income reported for CMBS loans tends to be overstated relative to actual property income. The income overstatements overstatement is measured as the discrepancy between the underwritten NOI and the realized NOI in the year of CMBS issuance.

the instrumental variable. The coefficient for opioid distribution OP is 0.0189, indicating that higher levels of opioid distribution are associated with a significant increase in the probability of loans becoming delinquent for 60 days or more. This initial result demonstrates a strong correlation between opioid abuse and financial instability in local markets, particularly in areas where opioid availability is widespread.

3.2 Instrumental Variable Analysis

One key challenge in identifying the causal effect of opioid distribution on mortgage delinquency is the potential for endogeneity. Economic conditions that lead to increased opioid abuse—such as high unemployment or poverty—may also increase the likelihood of loan defaults, making it difficult to disentangle the two effects. To address this, we use an instrumental variable (IV) approach, leveraging payments from opioid-related pharmaceutical companies to physicians as an instrument for opioid distribution. These payments create financial incentives for doctors to prescribe more opioids, thus increasing the availability of opioids in the market. Crucially, these payments are driven by pharmaceutical marketing strategies and are not influenced by local economic conditions, making them an exogenous predictor of opioid distribution (Hadland et al., 2019; Engelberg, Parsons and Tefft, 2014). This allows us to isolate the variation in opioid distribution that is unrelated to local factors driving mortgage delinquency.

In the first stage of the IV analysis, we use physician payments to predict opioid distribution per capita. The F-statistic of 47.7 confirms that pharmaceutical payments are a strong predictor of opioid availability. This first stage isolates the exogenous variation in opioid distribution, mitigating concerns about reverse causality or omitted variables. Column 2 of Table 2 shows that higher levels of physician payments, which encourage opioid prescriptions, lead to increased opioid availability in the local market. The coefficient for physician payments is both positive and statistically significant, confirming that the

exogenous variation in opioid distribution, as driven by pharmaceutical marketing strategies, is a key factor in explaining higher mortgage delinquency rates.

In the second stage, we use the predicted values of opioid distribution to estimate its effect on mortgage delinquency. The underlying hypothesis is that opioid abuse imposes substantial financial strain on individuals and communities. People struggling with addiction often experience job loss, reduced income, and increased healthcare costs, impairing their ability to meet financial obligations such as mortgage payments. In regions where opioid addiction is prevalent, multifamily housing properties may experience higher vacancy rates, while reduced local consumer spending negatively affects retail businesses. This increased financial pressure on property owners leads to a higher likelihood of mortgage delinquencies in both residential and commercial real estate sectors.

The result in Column 3 of Table 2 confirms the predication: a one standard deviation increase in opioid distribution (32 pills per Capita, 0.32 after scaling) leads to a 0.42 percentage point increase in the likelihood of loans becoming delinquent for 60 days or more. Given that the baseline delinquency rate is 0.28%, this increase is considerable, more than doubling the delinquency rate to 0.70%. These findings are consistent with prior research demonstrating the broader economic spillover effects of opioid abuse, including negative impacts on local labor markets and financial performance (Custodio, Cvijanovic and Wiedemann, 2023; Cornaggia et al., 2022).

In addition to the primary results, the control variables provide valuable insights into the broader economic dynamics affecting loan performance. Areas with higher employment and more diversified business sectors, as captured by the Herfindahl index, tend to experience lower delinquency rates, as these regions are better able to absorb economic shocks. Conversely, regions with higher proportions of the population without health insurance or with significant poverty tend to exhibit higher delinquency rates, as households in these areas are more vulnerable to financial distress.

Loan performance is also shaped by both demographics and loan characteristics. ZIP

codes with more working-age individuals (20–60 years) tend to have lower delinquency rates due to greater financial stability, while areas with more elderly residents or households with high rent-to-income ratios face higher default risks, exacerbated by economic shocks such as the opioid crisis. Riskier loan features, such as high loan-to-value (LTV) ratios, interest-only structures, and overstated net operating income (NOI) at securitization, further increase the likelihood of default, as supported by previous research (Griffin and Priest (2023)).

In summary, both the OLS regression and instrumental variable analysis provide robust evidence that opioid abuse, as instrumented by physician payments, has a direct and causal effect on mortgage delinquency in commercial real estate loans. This result highlights the far-reaching economic consequences of the opioid crisis, showing that it not only affects public health but also contributes to financial instability in local real estate markets. By addressing the root causes of opioid abuse, policymakers can potentially reduce both the human and economic toll of the crisis, stabilizing local economies and reducing the risk of financial distress.

[Place Table 2 about here]

3.3 Robustness Tests

To ensure the robustness of our findings regarding the impact of opioid distribution on commercial mortgage delinquency, we conduct a series of additional tests that explore alternative measures of delinquency and opioid distribution, as well as geographic variations and demand-side proxies. These tests help validate that our primary results hold across different specifications, confirming the stability and reliability of our conclusions.

Alternative delinquency measure - Instead of using the 60-day delinquency threshold, we substitute it with 30-day and 90-day delinquency thresholds. Table 3 presents the results that show that the positive relationship between opioid distribution and delinquency is robust between different measures of delinquency. The coefficients remain positive and statistically significant, indicating that the opioid distribution consistently increases the likelihood of loan delinquencies, whether measured at a 30-day or 90-day threshold. This finding is economically intuitive, as the financial stress caused by opioid abuse can affect borrowers at varying stages of delinquency. Opioid abuse leads to immediate financial distress, potentially disrupting timely loan payments within the first 30 days. As abuse continues, the financial burden worsens, significantly increasing the risk of severe delinquency (90 days or beyond), with a 9 basis point difference.

[Place Table 3 about here]

Alternative measurements of opioid distribution - One potential concern is that different opioid drugs vary in potency, and simply counting pills may not capture the true magnitude of opioid consumption. To address this, we compute the annual distribution of milligram equivalents of morphine (MME) per ZIP code, standardizing the strength of opioids based on MME values for each pill. For example, oxycodone is 50% stronger than hydrocodone and therefore has an MME multiplier of 1.5. Adjusting for the strength of opioids, this approach provides a more accurate reflection of opioid availability in a given area. Column 1 of Table 4 shows that even after standardizing opioid strength, the association between instrumented opioid distribution and mortgage delinquency remains strong and statistically significant. This suggests that the relationship between opioid distribution and delinquency is not driven by the type of opioid drug consumed, but rather by the overall volume of opioid consumption, which drives economic distress.

Time lags of the effect - We then account for potential time lags in the effect of opioid distribution on delinquency by introducing lagged variables. Opioid abuse may not immediately result in financial distress, as addiction could initially cause a gradual decline in job performance or income, followed by more severe economic consequences. To capture these delayed effects, we include one-year and two-year lagged opioid distribution variables in our model to capture these delayed effects. The results, as shown in columns 2 and 3 of Table 4, are robust across both lag periods. The one-year and two-year lagged opioid distribution coefficients are positive and statistically significant, indicating that the economic impact of opioid abuse can persist over time. This highlights the prolonged and cumulative nature of opioid-induced financial distress.

Geographical boundary of opioid distribution - We also refine our geographic approach to opioid distribution by calculating opioid pills shipped to pharmacies within 1 km and 3 km radii of each property. This adjustment accounts for the possibility that opioid users may visit pharmacies outside of their residential ZIP codes, but still within close proximity of their homes or workplaces. As illustrated in Appendix A1, we utilize GIS software to delineate the coverage of ZIP codes within 1 km and 3 km of the property location. It should be noted that this ring can encompass multiple ZIP codes. For example, in Figure A1, the opioid pills within the radius are calculated as the sum of three segments: the pills in the dotted area, the slash-lined area and the grid area. For the dotted area, the number of pills is determined by dividing the total number of pills for ZIP code 02090 by its total area and then multiplying by the size of the dotted area. Similarly, for the slash-lined area, the pill count is calculated by dividing the total pill count for ZIP code 02026 by its total area and then multiplying by the size of the slash-lined area. Finally, for the grid area, the total pill count for ZIP code 02062 is divided by its total area and then multiplied by the size of the grid area. Subsequently, all variables are aggregated from ZIP code level to the 1 km or 3 km ring area by weighting the ZIP code level value by the portion of the ZIP code covered within the radius.

The results, as reported in columns 4 and 5 of Table 4, reveal that the effect of opioid distribution on mortgage delinquency decreases with distance. The coefficient for opioid distribution in the radius of 1 km remains statistically significant, but its magnitude is smaller than that at the ZIP code level. For the 3 km radius, the effect becomes statistically insignificant, suggesting that the spatial influence of opioid supply on mortgage performance is localized. This finding supports the notion of spatial decay, where the proximity of opioid

availability plays a crucial role in its impact on local economic outcomes. From an economic perspective, this spatial concentration of effects may reflect how localized patterns of opioid abuse directly influence the financial health of borrowers and property markets within a small radius.

[Place Table 4 about here]

Demand-side measure of opioid abuse - We consider a demand-side measure of opioid abuse, focusing on opioid prescription rates rather than supply-side distribution data. The prescription rate serves as a proxy for local opioid abuse and captures the demand-driven aspect of the opioid crisis. Using data from the Centers for Disease Control and Prevention (CDC), we obtain annual opioid prescription counts at the county level per 100 people. It is defined as the count of annual opioid prescriptions at the county level per 100 people. These data are sourced from Centers for Disease Control and Prevention reports, derived from IQVIA Xponent starting in 2006. IQVIA Xponent gathers opioid prescriptions identified by national drug codes from approximately 49,900 retail (nonhospital) pharmacies, covering nearly 92% of all retail prescriptions in the United States. However, since these data are only accessible at the county level, we employ this measurement as a robustness test. Column 1 of Table 5 shows that counties with higher opioid prescription rates are associated with significantly higher delinquency rates. A one-standard deviation increase in the opioid prescription rate (36.2 per 100 persons) corresponds to a 0.19 percentage point increase in the 60-day delinquency rate, further validating the robustness of our findings. This result is consistent with previous research that has linked higher opioid prescription rates with increased financial distress in local markets. The demand-side dynamics of opioid abuse, driven by over-prescription, contribute significantly to the mortgage delinquency.

Alternative Instrumental Variable - We further strengthen this analysis employing an instrumented variable for the county-level opioid prescription rate, following methodologies used in previous studies Cornaggia et al. (2022) and Custodio, Cvijanovic and Wiedemann

(2023). By focusing on the distribution channels and using opioid pills sold through pharmacies with the least oversight as the instrument, we ensure that the observed effects are driven by exogenous factors rather than local demand. We first aggregate the distribution of opioids from the ZIP code level to the county level and regress the opioid prescription rate on the pill concentration. All control variables are also aggregated to the county level. The results of the two-stage regression are reported in columns 2 and 3. In column 2, we observe that counties with a higher level of pills sold in pharmacies exhibit a significantly higher prescription rate.

This finding is consistent with previous literature (Cornaggia et al., 2022; Custodio, Cvijanovic and Wiedemann, 2023). The F statistic is 442, confirming the validity of the instrument. In the second stage, we observe a significant positive relationship between the instrumented prescription rate and delinquency. A one standard deviation increase in the opioid prescription rate (29.06 per 100 capita, based on the instrumented opioid prescription rate) is associated with a 0.14 percent increase in the delinquency rate. This effect is comparable in magnitude to the findings in the previous literature. For example, Custodio, Cvijanovic and Wiedemann (2023) found that a one standard deviation increase in the prescription rate (27.1 prescriptions per 100 people for the 5-year lagged sample) was associated with a 22.69 percentage point higher rate of change in delinquent mortgages. Beginning with a 2.41% mortgage delinquency rate in their sample, the delinquent mortgages would have only decreased to 1. 34% instead of 0. 80%. In other words, delinquent mortgages would increase by 67.5% with a one standard deviation increase in the prescription rate. In our study, focusing on commercial mortgage loans, the delinquency rate would increase by 59% (from 0.28% to 0.45%).Thus, the magnitude is comparable.

[Place Table 5 about here]

3.4 Difference-in-Differences Analysis

To further validate our results and strengthen the causal link between opioid abuse and mortgage delinquency, we use the variation in opioid use induced by the staggered adoption of state laws that limit opioid prescriptions. The staggered nature of these laws, implemented at different times in states, creates a natural experiment. This allows us to estimate the impact of opioid abuse on mortgage delinquency by comparing the changes in mortgage default rates before and after the passage of the law, in counties affected by the law (treated group) versus those that were not (control group).

3.4.1 Effects of Opioid Limiting Laws

We implement a generalized difference-in-differences (DID) framework to measure this effect. The DID model enables us to isolate the impact of opioid-limiting laws by controlling for unobserved factors that are constant over time within zipcodes or counties (such as regional characteristics) and factors that change over time but affect all zipcodes or counties equally (such as national economic trends). The regression specification is as follows:

$$y_{i,j,t} = \beta D_{i,j,t} + \delta X_{i,t} + \tau_t + \omega_j + \upsilon_{i,j,t}$$
⁽²⁾

 $y_{i,j,t}$ represents the delinquency status of a loan *i* from state *j* at time *t*. The key independent variable, $D_{i,j,t}$, is a treatment indicator that equals 1 for properties in states after the adoption of the opioid-limiting law, and 0 otherwise. The vector $X_{i,t}$ controls for other property-level and economic factors, τ_t captures time fixed effects to control for macroeconomic shocks, and ω_j accounts for state fixed effects to control for state-specific factors. The error term $v_{i,j,t}$ captures any remaining unobserved factors affecting delinquency.

The results, as shown in column 1 of Table 6, indicate that the coefficients on $D_{i,j,t}$ is significantly negative. It suggests that after opioid limiting laws were passed, the probability

of mortgage delinquency decreased by about 19 bps. This indicates that areas that enacted these laws saw a small but meaningful reduction in mortgage defaults. Economically, this outcome makes intuitive sense. The implementation of opioid prescription limits likely leads to a reduction in opioid misuse and addiction, which in turn improves the financial stability of affected borrowers. Reducing opioid abuse alleviates some of the economic burden on households, such as job loss, medical expenses, and the associated decline in productivity. These improvements in household financial conditions lead to a better mortgage payment behavior, resulting in fewer delinquent commercial mortgage loans. Furthermore, businesses and landlords in opioid-stricken regions likely see benefits from improved tenant income stability and reduced vacancy rates, especially in multifamily housing properties.

3.4.2 Matched Sample Analysis

One concern with the difference-in-differences analysis is the potential for selection bias. States that adopt opioid-limiting laws may systematically differ from those that do not, in ways that could confound the results. For example, states with higher levels of opioid misuse may be more likely to pass such laws, or they may have underlying economic and demographic differences that make them more susceptible to opioid-related economic stress. These differences between the treated and control states could bias the estimates.

To address for this potential bias, we apply propensity score matching to ensure that treated states (those that passed opioid-limiting laws) are compared to similar untreated states. We match states based on state-level economic and demographic conditions, including opioid use, the total number of jobs, business concentration measured by the Herfindahl index of employments across three digital industry sectors, the age 20-60 ratio, the age over 60 ratio, male population to female ratio, disability rates, the proportion of individuals lacking public or private health insurance coverage, poverty rates, unemployment rates, median rental costs, and total number of physicians in the state. For states in the year following the passage of the law, we use their economic and demographic conditions from

previous years to ensure that the matching results are not retroactively influenced by the implementation of the law. We use nearest-neighbor matching to pair each treated state with its closest match from the control group. This reduces the risk of bias from differences in state-level characteristics.

After matching, the sample is restricted to properties located in 34 states. We then perform Equation (2) using the matched sample. As shown in Column 2, Table 6, the coefficient for the post-law dummy remains statistically significant, but the magnitude of the coefficient is reduced from 0.0019 to 0.0009. This indicates that even after controlling for potential selection bias, the passage of opioid limiting laws has a clear and substantial effect on reducing mortgage delinquency rates. The reduction in the coefficient suggests that some of the observed effects in the unmatched sample may have been driven by differences between the treated and control states, but the overall finding remains robust.

[Place Table 6 about here]

3.4.3 Effects of Opioid Limiting Laws: Dynamics

Since the law is passed in various calendar year-month in different states, it is important to capture the dynamic effects of the law over time. We implement a dynamic staggered DID model, which allows us to examine how the impact of the law evolves in the months leading up to and following its implementation. The dynamic staggered DID model is based on the matched sample as follows:

$$y_{i,j,t} = \sum_{k=-12, k\neq -1}^{12} \beta^k D_{i,j,t}^k + \delta X_{i,t} + \tau_t + \omega_j + \upsilon_{i,j,t}.$$
(3)

where $D_{i,j,t}^k$ are relative period indicators, equal to 1 for properties in month *k* relative to the law's passage (e.g., $D_{i,j,t}^{-2}$ indicates two months before the law, $D_{i,j,t}^{12}$ indicates 12 or more

months after, and $D_{i,j,t}^{-12}$ indicates 12 or more months before). We omit the period immediately before the law's passage ($D_{i,j,t}^{-1}$) to avoid multicollinearity.

Figure 4 illustrates the dynamics of the treatment effect, β^k , over time. The squares indicate the expected value of β^k and the lines indicate a 95% confidence interval. As illustrated in Figure 4, the delinquency rate declines significantly in the second, third and from the fifth to the eleventh month after the passage of the laws in the treated states, relative to the control group. In the eleventh month after the passage of the law, the 60day delinquency rate decreased by 10 basis points. These dynamic results provide further evidence that the reduction in delinquency is not a short-term response to the law, but a sustained improvement in financial stability following the reduction in opioid abuse.

[Place Figure 4 about here]

3.4.4 Addressing Issues with Staggered DID

However, recent studies (eg, Callaway and Sant'Anna (2021), Goodman-Bacon (2021), Sun and Abraham (2021), Borusyak, Jaravel and Spiess (2024)) have raised concerns about potential biases in staggered DID models, particularly the issue of negative weights. These biases arise in settings with a staggered treatment timing, especially when treatment effects vary between cohorts or time periods. Negative weights can distort the estimation of causal effects when the timing of treatment varies and when the effects of treatment are heterogeneous between groups. To address this issue within the Two-Way Fixed Effects framework, we employ a fully saturated model that includes interaction terms, capturing cohort-specific treatment effects over time. This approach helps to ensure that the estimated effects accurately reflect the variations in the timing and impact of treatment. The revised model is as follows:

$$y_{i,j,t} = \sum_{c \in C} \sum_{k=-12, k \neq -1}^{12} \beta^{k,c} \mathbf{1}\{c_{i,t} = C\} D_{i,j,t}^{k,c} + \delta X_{i,t} + \tau_t + \omega_j + \upsilon_{i,j,t}.$$
(4)

where $1{c_{i,t} = C}$ is an indicator function for whether loan *i* located in the state belongs to cohort $c \in C \equiv \{\text{March 2016, April 2016, May 2016, June 2016, October 2016, November 2016, February 2017, March 2017, April 2017, May 2017, June 2017, July 2017, December 2017, March 2018, May 2018, November 2018}, based on the timing of the law's adoption in that state.$

As a result, Equation (4) produces an *KC* matrix of time-varying cohort specific coefficient $\beta^{k,c}$. We recover the interacted-weighted estimator of the treatment effect in relative time *k* as:

$$A^{k} = \sum_{c \in C} w^{k,c} \beta^{k,c}.$$
(5)

where w^{kc} is the weight of cohort c at event time. Following Sun and Abraham (2021), we determine the weight for each $\beta^{k,c}$ as the sample share of each cohort in C in the relative time period. We bootstrap the procedure 1000 times with replacement to obtain standard errors for appropriate statistical inference following the bootstrap method by Agarwal et al. (2021). The dynamics of A^k is illustrated in Figure 5, where the squares indicate the expected value of A^k a and the lines indicate a 95% confidence interval. We observe similar patterns as in the standard dynamic staggered DID analysis. The reduction in delinquency rates persists across different cohorts and time periods, with the most pronounced effects occurring two, three, and eleven months after the law's passage. Using this more granular approach, we further validate that the decrease in delinquency is driven by the reduction in opioid abuse following the prescription limits.

[Place Figure 5 about here]

4 Channel Analysis: Opioid Abuse and Local Economy

4.1 Performance of Underlying Property

To support our hypothesis that opioid abuse negatively impacts the performance of underlying assets, we further analyze loan performance by examining changes in net operating income ($\Delta NOI_{i,t}$) and occupancy rates ($\Delta OCC_{i,t}$) in relation to opioid abuse. We use opioidrelated payments as an instrumental variable to address potential endogeneity issues, similar to the method used in previous sections. By focusing on changes in NOI and occupancy rates, we effectively control for unobserved, time-invariant factors linked to property and community characteristics, allowing us to isolate the effects of time-varying variables such as local economic conditions at the ZIP code level. Thus, we exclude the characteristics of the time-invariant properties. However, since preferences for building types (e.g., the possibility of remote working reducing office demand) and regional economic conditions may evolve at different growth rates, we still control for property type, state, and year-month fixed effects. This allows us to capture systematic variations in property investment performance in different types, locations, and time periods.

The results, presented in Table 7, show a statistically significant negative relationship between opioid pill distribution and both NOI and occupancy rates. In areas with a higher opioid distribution, NOI and occupancy rates decrease, confirming that opioid abuse adversely affects property performance. This decline in NOI suggests that opioid abuse leads to reduced rental income or increased operating expenses, as tenants impacted by opioid misuse may struggle to make consistent payments. Furthermore, the drop in occupancy rates indicates that opioid abuse may also be driving higher tenant turnover or vacancy rates, likely due to financial distress among renters.

The control variables provide additional insight into the dynamics of loan performance. For example, the level of employment (*Emp*) positively impacts ΔNOI , since a strong local labor market contributes to the financial stability of tenants, improving property income. Business concentration (*EmpConcen*) also positively correlates with NOI, suggesting that economic specialization or diversification may provide an economic premium that benefits loan performance (Liu, Zheng and Zhu, 2022). Demographics such as the proportion of individuals over 60 years old show a positive influence on NOI, likely due to the stability that retirees or older populations bring as tenants. On the other hand, variables such as the poverty rate (*PovertyRate*) and the unemployment rate (*Unempl.*) have significant negative effects on both NOI and occupancy rates, reflecting the economic vulnerabilities that undermine property performance in regions struggling with poverty and unemployment. The presence of total physicians (*TotalPhysicians*) has a small but significant positive effect on NOI, indicating that a better healthcare infrastructure may mitigate some of the negative impacts by providing stability to the local population. Overall, these results highlight the multifaceted nature of the impact of opioid abuse, showing how it intersects with local economic and demographic conditions to influence commercial property outcomes.

Overall, this loan-level analysis confirms the transmission mechanism: areas with higher opioid abuse potential experience a reduction in the NOI of collateralized properties, increasing the risk of loan defaults. This finding highlights the economic ripple effects of opioid abuse, showing how it can undermine the performance of commercial real estate assets.

[Place Table 7 about here]

4.2 Sales Volume of Local Retail Trade Sectors

The adverse impact of opioid overdoses highlights a channel through revenue generated by the property: excessive use of opioid pills reduces household spending on living expenses and goods, either due to the cost of the pills themselves or through reduced income and potential job losses. This, in turn, leads to a decrease in the income generated by properties, as tenants may delay or reduce their rental payments. As a result, loan delinquency rates increase.

To provide more direct evidence, we examine the impact of opioid overdoses on local household consumption, measured by the volume of retail sales per store at the ZIP code level, and investigate whether consumption or sales volume affects property revenue. The sales volume data for establishments across zip codes is sourced from the Alex database. Sales volume is calculated based on establishments within the retail trade sector (Sector G in SIC codes) located in each zip code⁶. The zipcode-level control variables are the same as in the previous section. Additionally, we control for the total population and apply county-by-year fixed effects.

The results, presented in Panel A, Table 8, show how opioid distribution influences retail sales and reveal the economic ripple effects of opioid abuse on commercial properties that depend on consumer spending. The data indicates that an increase in opioid distribution is negatively correlated with sales in three categories: home-related expenditures, other consumer goods, and dining expenditures. Specifically, a one standard deviation increase in opioid distribution is associated with declines of 14.3%, 12.0% and 9.2% in spending on home-related expenses, other consumer goods (such as sporting goods, jewelry, books, etc.) and dining services, respectively.

Essential basic products, including food stores and other necessities such as clothing (Columns 1 and 2, Panel A, Table 8), are basic, necessity-driven items. As a result, this segment shows relative resilience, and we do not observe a significant impact of opioid overdoes on their sales volume. As these goods are essential for daily survival, their demand remains relatively inelastic even during economic hardship. The decrease in sales is more likely due to consumers opting for cheaper brands, smaller quantities, or discount stores rather than eliminating these purchases altogether. This behavior stabilizes the demand for

⁶We categorize the retail trade sector into six segments: groceries (54 Food Stores); other essential basics (56 Apparel & Accessory Stores, 5912 Drug Stores and Proprietary Stores, 5921 Liquor Stores, and 5331 Variety Stores); home-related spending (52 Building Materials & Gardening Supplies, 57 Furniture & Home Furnishings Stores); other consumer goods (594 Miscellaneous Shopping Goods Stores, 598 Fuel Dealers, 599 Other Retail Stores, and 5311 Department Stores); dining (5812 Eating Places); and alcoholic beverages (5813 Drinking Places - Alcoholic Beverages)

living goods, which limits the extent of the decline compared to other more discretionary retail categories. Consequently, while the impact is negative, commercial properties that host these tenants may experience less volatility compared to those that rely on more discretionary spending sectors.

Interestingly, our analysis does not reveal a significant decrease in spending on alcoholic beverages as opioid distribution increases (column 6, Panel A, Table 8). This finding can be attributed to the well-documented interrelationship between alcohol and opioid use, where the two substances are often co-consumed or exhibit complementary patterns of use. This behavioral overlap may explain the sustained expenditure on alcohol despite the increased availability of opioids.

Dining (Column 5, Panel A, Table 8) experiences a more pronounced decline in sales, reflected in a coefficient of -0.5748. Dining services, such as restaurants and cafes, are not neo-negligible and therefore highly elastic. Consumers can easily reduce these expenses when faced with financial stress. As opioid distribution increases, consumer spending on dining out decreases substantially, demonstrating the elasticity of this category. This drop has significant implications for commercial properties that specialize in food services, as these tenants rely on discretionary income, and any reduction in consumer spending capacity directly impacts occupancy rates and revenue.

Home and furniture items, as well as other consumer goods such as sporting goods, books, jewelry, and stationery (Columns 3 and 4, Panel A, Table 8) are the most severely affected. These items are highly discretionary, as spending on home improvements and furniture is often postponed or canceled during financial difficulties. When opioid abuse increases, households tend to prioritize these nonessential expenditures, resulting in a significant contraction in this segment. Commercial properties hosting these tenants, such as furniture showrooms or home improvement centers, can face severe revenue losses, increasing the risk of mortgage delinquency as these tenants struggle to meet rental obligations. The findings further highlight the channel through which opioid abuse leads to a decrease in

household spending in all sectors, leading to a broad contraction in local economic activity.

[Place Table 8 about here]

We also examine how local consumption influences loan performance. Loan performance is assessed using three metrics: the change in net operating income (NOI) since securitization (Column 1, Table 9), the change in occupancy since securitization (Column 2, Table 9), and 60-day delinquency rates (Column 3, Table 9). Local consumption is measured by the aggregate sales volume in all sectors listed in Panel A, Table 8.

As expected, we find that retail sales volume is positively associated with changes in NOI and occupancy, while negatively associated with delinquency rates. Altogether, the findings in Panel A, Tables 8 and 9 further corroborate our proposed mechanism: opioid abuse negatively impacts household consumption, as evidenced by reduced sales volumes in the local retail sector. This decline in household spending on living expenses and goods leads to delayed or diminished rental income received by the landlord. Consequently, landlord's ability to service their debt is adversely affected, as reflected in the increased probability of default on loans secured by these properties.

[Place Table 9 about here]

4.3 Neighborhood Appeal

We also test the aforementioned channel by examining neighborhood attractiveness, as the performance of commercial properties is strongly influenced by the appeal and amenities of the surrounding community. To assess the impact of opioid abuse on neighborhood attractiveness, we use data from the National Neighborhood Data Archive (NaNDA), focusing on the number of establishments in various amenity sectors at the census tract or zip code level. The amenity categories we focus on include the number of schools (both private and public elementary and secondary schools), grocery stores, other retails (clothing and shoe stores,

furniture and appliance stores, music stores, hardware and garden stores, department, variety and other general merchandise stores), dining services (restaurants, eating places and drinking places), physician services (all ambulatory health care services, all physicians, all nursing and residential care facilities) and leisure facilities (museums, libraries, amusement parks, golf, skiing, boating, fitness, bowling, and others). The number of establishments is recorded annually from 2003 to 2017. Therefore, our analysis of neighborhood amenities covers the period 2011 to 2017.

The results, presented in Panel B, Table 8, reveal how opioid-related issues can erode neighborhood desirability, potentially affecting commercial properties that depend on a vibrant local community. Zipcodes with an opioid overdose exhibit a significantly lower number of schools, living services, dining services, and leisure services. All else being equal, a one-standard deviation increase in opioid distribution is associated with 44.9% fewer eating and drinking places, 31.6% fewer entertainment facilities, 19.8% fewer grocery stores, 28.7% fewer retail stores, and 14.7% fewer elementary and secondary schools.

The insignificant coefficient for opioid distribution in healthcare facilities (Column 1, Panel B, Table 8) indicates that a higher opioid distribution does not necessarily correlate with a larger number of healthcare facilities. Although more facilities could be expected in response to rising health issues, the economic strain caused by opioid abuse probably makes it difficult for healthcare providers to operate, especially in rural areas. Opioid-related cases often drive up uncompensated care costs and overwhelm hospitals, particularly in financially vulnerable communities. Furthermore, staffing challenges and burnout further undermine these facilities, leading to closures, such as the closure of Hancock County Hospital in Tennessee in 2019 due to financial strain from opioid-related cases. In contrast, areas with higher employment levels show a positive correlation with healthcare facilities, underscoring the importance of economic stability. Although demand-driven factors can play a role in maintaining access to healthcare facilities, availability may still be influenced by local economic conditions. Dining amenities (Column 2, Panel B, Table 8), such as restaurants and cafes, decline significantly as opioid distribution increases, reflecting the negative impact of opioid abuse on discretionary spending. As consumer spending declines, many dining establishments close, reducing the count of such amenities. The positive relationship between employment levels and dining amenities suggests that stable employment helps sustain these businesses by maintaining consumer spending power. However, the negative coefficient for business concentration indicates that areas with less economic diversity are more vulnerable, as they lack the economic resilience needed to support dining services during downturns.

Entertainment amenities (Column 3, Panel B, Table 8), including museums, fitness centers, and recreational facilities, also decrease significantly with increasing opioid distribution. These amenities rely on discretionary income and as opioid abuse increases, residents reduce spending on entertainment, leading to closures. Higher employment levels positively correlate with entertainment facilities, demonstrating the importance of economic stability in maintaining non-essential amenities. ZIP codes with a larger population of people over 60 years old are positively associated with entertainment venues, probably reflecting the preferences of this demographic for social and recreational activities. However, areas with concentrated business environments are more susceptible to losing these amenities.

The availability of grocery stores and other retail stores (Columns 4 and 5, Panel B, Table 8) is negatively affected by opioid distribution. Despite the typically inelastic demand for groceries and other essential basics, economic decline and population displacement linked to opioid abuse reduce the number of stores in affected areas. Regions with a higher number of physicians tend to have more stores, which shows that healthcare access and economic stability are crucial to sustaining essential services. However, higher poverty and unemployment rates correlate with fewer grocery and retail stores, reinforcing how economic distress undermines even basic neighborhood amenities.

Schools (Column 6, Panel B, Table 8), critical for neighborhood stability, also decrease significantly as opioid distribution increases. The reduction in schools is likely the result of

the decline in population and reduced funding as economic conditions worsen in affected areas. In contrast, access to healthcare and a higher number of physicians are positively correlated with school availability, emphasizing the role of comprehensive healthcare access in supporting neighborhood infrastructure. However, higher poverty and unemployment rates significantly decrease the number of schools, showing how opioid-related economic hardships degrade educational resources and neighborhood quality.

The findings of Panel B, Table 8 illustrate the far-reaching impact of opioid abuse on neighborhood amenities, leading to the erosion of neighborhood appeal. The reduction of both essential and non-essential services—from healthcare facilities to dining and entertainment options—indicates a widespread decline in neighborhood quality. This deterioration has direct consequences for commercial properties, as their ability to attract tenants and maintain property values is closely related to the vibrancy of their surroundings. Properties in areas with declining amenities face higher risks of vacancy and income instability, as businesses struggle to operate in less attractive neighborhoods. Policymakers should prioritize economic diversification and access to healthcare to mitigate these effects, stabilize communities, and protect local real estate markets from the broader impacts of opioid abuse.

Following the approach in the previous section, we examine whether neighborhood appeal influences loan performance. Neighborhood attractiveness is quantified by the density of amenities across all categories listed in Panel B, Table 9. As expected, we find that the presence of neighborhood amenities is positively associated with changes in NOI and negatively associated with delinquency rates. These results further support our proposed mechanism: excessive opioid use undermines the desirability of the neighborhood, which can reduce the income generated by properties in the area. Reduced or delayed tenant rent payments weaken the property's debt service capacity, thereby increasing the likelihood of loan defaults in these neighborhoods.

5 Heterogeneity: Property Type and Local Condition

5.1 Role of Property Type

We provide an in-depth examination of how opioid distribution impacts mortgage delinquency across different types of properties: residential (e.g., multifamily properties), retail, office and other. As shown in Table 10, the positive correlation between mortgage delinquency and opioid pill distribution is primarily due to residential and retail buildings. This validates the hypothesis: prolonged opioid use can reduce family spending or lead to difficulties in paying rent, resulting in mortgage defaults and vacancies in these properties. This could be caused by the increase in spending on opioid pills. It can also be explained by the fact that opioid use can lead to decreased labor productivity, resulting in decreased household income and possible job loss. Consequently, families may be forced to reduce their spending on living and goods. For example, Jansen (2023) show that a higher default rate of subprime auto loans with increases at the county level in opioid abuse, which implies a reduction in households' ability to pay off the loan or consume. Moreover, opioid abuse can diminish the appeal of the neighborhood through residential sorting (Yang et al., 2022). Consequently, neighborhoods affected by this issue may become less attractive to higher-income households, who may opt not to reside there(Han, 2010).

In contrast, office properties show a weaker relationship between opioid distribution and mortgage delinquency, suggesting that office properties are less directly affected by opioid abuse compared to the residential and retail sectors. Office properties tend to have more stable long-term leases and are less reliant on local consumer behavior. In addition, the impact of opioid abuse on businesses that occupy office spaces might not be as immediate or as direct as that of retail or residential tenants. The lower sensitivity of office properties may also be attributed to the fact that these properties often cater to businesses and firms that are not as susceptible to local economic conditions or consumer spending patterns. However, this finding does not imply that office properties are immune to the broader economic effects of opioid abuse; it merely suggests that the transmission mechanism for delinquency in this sector is less direct and may have impacts over longer periods or through indirect channels such as regional economic downturns.

The other category includes property types that do not fall within the residential, retail, or office classifications. The coefficient of distribution of opioids in this category is also not statistically significant. This finding indicates that, while opioid distribution does have a positive relationship with mortgage delinquency in this category, the effect is not as pronounced or clearly defined as in the residential and retail sectors. The mixed results for this category may be due to the heterogeneity of property types within it. This group likely includes properties such as industrial sites, hospitality, and other specialized real estate, each of which may respond differently to opioid-related economic pressures. For instance, industrial properties may be less affected by local opioid abuse, while hospitality properties may experience a decline in occupancy or revenue if opioid misuse reduces the area's appeal as a destination. The variability within this category could contribute to the lack of statistical significance, as the effects of opioid abuse may be more diffuse and harder to detect in a heterogeneous group of property types.

[Place Table 10 about here]

5.2 Role of Local Economic Conditions

Since our channel focuses on the reduction in household spending on living expenses and goods, we expect heterogeneous reactions to opioid abuse among households with different income or affordability levels. To explore this, we consider four proxies for aggregate household income or affordability in the local areas: the coverage of health insurance, the local job opportunities, and the rental cost as percentage of the total income, and whether the loan is an agency loan.

Table 11 highlights the moderating effects of health insurance coverage, employment

levels, rental costs, and loan type (agency vs. nonagency), providing insight into the specific mechanisms through which opioid abuse translates into financial distress. As shown in Column 1, the impact of opioid distribution on mortgage delinquency is higher in zip codes with a lower share of the population covered by health insurance. This finding is economically intuitive. In areas where commercial properties are dependent on tenants who lack health insurance, businesses can struggle to absorb the costs associated with opioid-related healthcare burdens. For example, in areas with low insurance coverage, employees may face higher medical costs, reducing their spending power and impacting businesses such as retail or service establishments. Additionally, the negative coefficient for the uninsured population itself highlights that regions with high uninsured rates are already vulnerable, making them even more susceptible to higher delinquency rates when compounded by the financial strain of opioid abuse

Furthermore, we also find that the adverse impact of opioid abuse on mortgage delinquency is stronger in zip codes with fewer jobs, as shown in column 2 of Table 11. In areas with fewer job opportunities, households are more likely to face job loss. Consequently, the reduction in living and goods spending due to opioid consumption may be more severe. This further confirms our proposed channel.

Moreover, we also observe that in zip codes where the median percentage of rental cost to total income is higher, mortgage loan default becomes more sensitive to the risk of opioid abuse. The results are reported in column 3, Table 11. This result is particularly relevant for multifamily properties, where rental affordability directly affects occupancy rates and NOI. In areas where rental costs represent a large share of income, multifamily property owners are especially vulnerable to the economic consequences of opioid abuse. When opioid use escalates, the ability of tenants to pay rent can decrease, resulting in higher vacancies or lower rental collections, which in turn negatively affects property cash flows and increases the likelihood of mortgage delinquency. The significant interaction effect underscores that areas with high rental burdens are more exposed to financial instability when compounded by opioid-related economic stress.

Lastly, we proxy the income and status of households by whether the loan is included in CMBS deals. Agency CMBS comprises pools of loans secured by multifamily or healthcare properties issued by a US government agency or federally chartered corporation, such as Fannie Mae, Freddie Mac, or Ginnie Mae. Government agencies, particularly Fannie Mae, focus on providing housing for the workforce, high-quality affordable housing, to families with annual incomes that are below or below the median income of the areas where they reside. As stated by Fannie Mae (2012), more than 85% of the multifamily units financed by Fannie Mae from 2009 to 2011 were affordable to these families. Thus, tenants or households living in properties sponsored by US government agencies are more likely to have lower incomes compared to those in properties with non-agency loans. Therefore, we use loans in the agency CMBS as a proxy for the income status of tenants/households. As shown in column 4 of Table 11, the adverse impact of opioid overdose is statistically significantly stronger in agency loans. This further confirms our channel that opioid abuse can lead to a reduction in consumption and spending, with this effect being more severe for low-income households.

[Place Table 11 about here]

5.3 Role of Local Demographic and Political Conditions

Next, we examine the impact of the opioid crisis on ethnic groups, as it may disproportionately affect more vulnerable populations, such as the Black community, which faces relatively limited access to healthcare and treatment and receives less government support (Britz et al., 2023). To measure ethnic composition, we use the share of individuals identifying as Black or African American alone, Asian American (including Asian alone, American Indian and Alaska Native alone), and Some Other Race alone.

We then interact these variables of the ethnic community with opioid use. The results,

presented in Column 1 of Table 12, show a significantly positive coefficient for the interaction variable with the Black and Asian community. According to Ivanich et al. (2021), in the recent opioid crisis, in 2016–2017, African Americans populations saw the highest increase (60.7%) in synthetic opioid-related deaths, followed by American Indian population (58.5%). This finding suggests that more vulnerable communities may experience a greater impact from opioid usage, suffering more severe negative consequences on the local economy. The economic burden of opioid addiction—such as reduced workforce participation and increased healthcare costs—may weigh more heavily on these communities, compounding existing inequalities.

We also consider the age composition of the community, as evidence shows that young people may be more vulnerable to opioid abuse. Therefore, we examine the share of the population aged 15 to 24 in the zip code and create an interaction variable. The results are reported in Column 2 of Table 12. As shown, the coefficient for the interaction variable is significantly positive, while the coefficient for the share of young people alone is not significant. This suggests that in communities with a higher proportion of young people, the increase in commercial loan delinquency is largely driven by opioid abuse.

Lastly, if the adverse effect of opioid usage on delinquency is driven by reduced consumption and/or income, we would expect this effect to be mitigated through social support. We approximate the level of social support by considering the state governance trifecta. When a single party controls the governorship and holds majorities in both the state senate and state house, it is more likely that the party can drive policy changes effectively, aligning the state's legislative direction with its ideological priorities. We hypothesize that democratic-controlled states provide better social support (Custodio, Cvijanovic and Wiedemann, 2023), thus reducing the negative impact of opioid use on mortgage delinquency.

To identify whether a state was controlled solely by the Democratic or Republican party, we used the State and Legislative Partisan Composition data for 2010, 2012, 2014, 2016, and 2018, published by the National Conference of State Legislatures. If control was divided, meaning the majority of seats in the state senate and state house were not held by the same party, we excluded the state-year from our sample. For instance, according to the 2010 report, AZ, FL, GA, ID, ND, SC, SD, TX, and UT were Republican-run states, while AR, CO, DE, IL, IA, ME, MD, MA, NH, NM, NY, NC, WA, WV, and WI were Democratic-run states.

Column 3 of Table 12 reports the results. As expected, in Democratic-run states, the negative effect of opioid abuse on mortgage delinquency is significantly mitigated. This suggests that policies or interventions implemented in these states may play a role in buffering the economic consequences of the opioid crisis. Similarly, (Custodio, Cvijanovic and Wiedemann, 2023) find that the adverse impact of opioids on house prices is less severe in Democratic-controlled states, further underscoring the role of state-level governance in mitigating the crisis's effects.

[Place Table 12 about here]

6 Impact of Opioid Abuse Exposure on CMBS Loans

In this section, we investigate whether the risk of exposure to opioid abusers is priced into CMBS loans. In regions with elevated opioid pill concentrations, there is a corresponding increase in loan defaults. Lenders who fail to identify properties with tenants vulnerable to opioid abuse face a higher credit risk, which can result in borrowers experiencing high borrowing costs and more stringent underwriting standards, potentially triggering broader consequences such as deteriorating credit conditions for borrowers.

Based on the instrumented opioid abuse and seemingly unrelated regression, we investigate the impact on initial spread, loan to value ratio and debt service coverage ratio simultaneously. The results of our analysis, presented in Table 13, confirm that CMBS loans secured by properties in ZIP codes with higher opioid concentrations have higher initial spreads. Column 1 of Table 13 shows that a one-standard deviation increase in opioid distribution is associated with a 0.7749 increase in the loan initial spread, which corresponds

to a 23 basis point increase. This finding aligns with economic intuition: lenders perceive properties located in opioid-affected areas as riskier due to the increased likelihood of tenant defaults and vacancies. Consequently, they demand higher spreads as compensation for taking on this elevated risk.

Additionally, we observe a significantly lower Loan-to-Value (LTV) ratio and a higher debt service coverage ratio in zip codes with higher opioid overdose rates. Specifically, a standard deviation increase in opioid concentration corresponds to a 2.7% decline in the LTV ratio and a 77.2% increase in the debt service coverage ratio. This suggests that opioid abuse has tangible effects on credit and loan supply in the local market, as lenders demand more equity or down payment from borrowers and higher income relative to debt obligations. These stricter lending criteria effectively limit borrowers' access to credit, further restricting their borrowing capacity. Such adjustments highlight the broader impact of opioid abuse on the local credit environment for commercial real estate investment, potentially deepening economic disparities in affected regions.

Furthermore, we find that local economic conditions, such as low employment, a lack of business concentration, higher poverty rates, higher rent-to-income costs, and a shortage of physicians, are reflected in the loan pricing. Similarly, local demographic conditions, such as a limited labor force between the ages of 20 and 60, are also factored into the pricing. We also observe a negative relationship between loan spread and debt service coverage ratio, a positive relationship between loan spread and LTV, as well as a negative relationship between the debt service coverage ratio and the loan-to-value (LTV) ratio, all of which align with our expectations. Additionally, income overstatement is associated with higher loan rates, consistent with previous findings by Griffin and Priest (2023). Longer term and interest only loan also show a higher spread.

Overall, the analysis confirms that geographic exposure to areas affected by opioid abuse results in higher borrowing costs and stricter lending standards for local investors, potentially limiting their access to credit and increasing their financial burdens. These challenges may create a negative feedback loop, as heightened financial burdens may contribute to higher rents, declining asset values, and reduced development activity, further eroding neighborhood livability and exacerbating socioeconomic disparities.

[Place Table 13 about here]

7 Conclusion

This paper provides empirical analysis linking the opioid epidemic with financial market spillovers through its impact on commercial real estate (CRE) loan performance. We use instrumental variables, propensity score matching, and difference-in-differences analysis to identify causal effects. By leveraging detailed loan-level data from the Commercial Mortgage-Backed Securities (CMBS) market and granular opioid distribution data, we demonstrate that opioid misuse significantly increases CRE loan delinquency rates. These effects are particularly pronounced in residential and retail properties, areas with weaker economic conditions, and communities with higher proportions of Black and Asian populations, younger individuals, or those in Republican states. Our findings reveal a novel economic externality of the opioid crisis, highlighting its far-reaching implications for local economies and financial stability.

Our study contributes to the growing body of literature on the intersection of public health crises and financial markets. Specifically, we build on research to examine how macroeconomic and localized shocks influence financial outcomes, such as mortgage defaults (see, e.g., Campbell and Cocco, 2015) and municipal finance (Cornaggia et al., 2022). By focusing on a novel driver, opioid misuse, our findings broaden the understanding of how socioeconomic shocks can propagate through real estate and financial markets. From a theoretical perspective, we extend existing models of default risk by identifying localized public health crises as drivers of systemic risk, affecting both property performance and mortgage stability. This intersection of health economics and financial systems provides a deeper framework for understanding how socioeconomic disruptions challenge financial stability.

Our analysis also demonstrates the effectiveness of public health interventions, such as prescription drug monitoring programs (PDMP), in mitigating the financial consequences of the opioid epidemic. States that adopted these measures saw significant reductions in mortgage delinquency rates, providing evidence that regulatory actions that address public health can have significant economic benefits. However, these interventions should be complemented by targeted economic policies, including job training programs, small business incentives, and financial assistance for regions hardest hit by the opioid crisis. Addressing the underlying socioeconomic vulnerabilities amplifies the impact of public health measures.

The implications of our findings are significant for policymakers, lenders, and investors. Addressing opioid misuse through a combination of public health and economic interventions could mitigate its negative effects on local economies and improve financial resilience. In addition, financial market participants should incorporate the risks associated with opioid-related economic disruptions into their risk assessment and pricing models. In doing so, they can better account for the systemic risks posed by localized public health crises, reducing the vulnerability of financial systems to such shocks.

This study advances the literature on the consequences of public health crises in the financial markets, opening new avenues for research. Future studies could explore similar dynamics in other sectors or regions, examine the long-term impacts of opioid-related interventions, and investigate how health and economic policies interact to influence financial resilience. By highlighting the interplay between public health and financial markets, this research underscores the need for multidisciplinary approaches to managing crises that extend beyond immediate human costs to systemic economic risks.

References

- **Agarwal, Sumit, Brent W Ambrose, Luis A Lopez, and Xue Xiao.** 2021. "Did the paycheck protection program help small businesses? Evidence from commercial mortgage-backed securities." *American Economic Journal: Economic Policy.*
- **Agarwal, Sumit, Brent W Ambrose, Yildiray Yildirim, and Jian Zhang.** 2024. "Risk retention rules and the issuance of commercial mortgage backed securities." *The Journal of Real Estate Finance and Economics*, 68(4): 684–714.
- Agarwal, Sumit, Gene Amromin, Souphala Chomsisengphet, Tim Landvoigt, Tomasz Piskorski, Amit Seru, and Vincent Yao. 2023. "Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinance program." *The Review of Economic Studies*, 90(2): 499–537.
- Agarwal, Sumit, Richard K Green, Eric Rosenblatt, and Vincent Yao. 2015. "Collateral pledge, sunk-cost fallacy, and mortgage default." *Journal of Financial Intermediation*, 24(4): 636–652.
- Aliprantis, Dionissi, and Kyle Fee. 2019. "Opioids and the labor market." Federal Reserve Bank of Cleveland Working Paper 18-07.
- **Borusyak, Kirill, Xavier Jaravel, and Jann Spiess.** 2024. "Revisiting event study designs: Robust and efficient estimation." *Review of Economic Studies*, rdae007.
- **Bradley, Michael G, Amy Crews Cutts, and Wei Liu.** 2015. "Strategic mortgage default: The effect of neighborhood factors." *Real Estate Economics*, 43(2): 271–299.
- Britz, Jacqueline B, Kristen M O'Loughlin, Tracey L Henry, Alicia Richards, Roy T Sabo, Heather G Saunders, Sebastian T Tong, E Marshall Brooks, Jason Lowe, Ashley Harrell, et al. 2023. "Rising Racial Disparities in Opioid Mortality and Undertreatment of Opioid Use Disorder and Mental Health Comorbidities in Virginia." *AJPM focus*, 2(3): 100102.
- **Callaway, Brantly, and Pedro HC Sant'Anna.** 2021. "Difference-in-differences with multiple time periods." *Journal of Econometrics*, 225(2): 200–230.
- **Campbell, John Y, and Joao F Cocco.** 2015. "A model of mortgage default." *The Journal of Finance*, 70(4): 1495–1554.
- **Cespedes, Jacelly C, Carlos R Parra, and Clemens Sialm.** 2024. "The effect of principal reduction on household distress: Evidence from mortgage cramdown."
- **Cornaggia, Kimberly, John Hund, Giang Nguyen, and Zihan Ye.** 2022. "Opioid crisis effects on municipal finance." *The Review of Financial Studies*, 35(4): 2019–2066.
- **Council of Economic Advisers.** 2019. "The underestimated cost of the opioid crisis." Executive Office of the President of the United States.

- Currie, Janet, Jonas Y Jin, and Molly Schnell. 2019. "US employment and opioids: Is there a connection?" *Brookings Papers on Economic Activity*, 2019(1): 207–255.
- Custodio, Claudia, Dragana Cvijanovic, and Moritz Wiedemann. 2023. "Opioid crisis and real estate prices." Available at SSRN 3712600.
- **De Chaisemartin, Clément, and Xavier d'Haultfoeuille.** 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review*, 110(9): 2964– 2996.
- Eichholtz, Piet, Eva Steiner, and Erkan Yönder. 2019. "Where, When and How Do Sophisticated Investor Respond to Flood Risk?"
- **Engelberg, Joseph, Christopher A Parsons, and Nathan Tefft.** 2014. *Financial conflicts of interest in medicine*. Vol. 2297094, SSRN.
- **Fernandez, Fernando, and Dijana Zejcirovic.** 2018. "The role of pharmaceutical promotion to physicians in the opioid epidemic." University of Vienna, Department of Economics.
- **Fisher, Gregg, Eva Steiner, Sheridan Titman, and Ashvin Viswanathan.** 2022. "Location density, systematic risk, and cap rates: Evidence from REITs." *Real Estate Economics*, 50(2): 366–400.
- **Fuster, Andreas, David Lucca, and James Vickery.** 2023. *Mortgage-backed securities.* Edward Elgar Publishing.
- **Gao, Janet, Hanyi Livia Yi, and David Zhang.** 2024. "Algorithmic Underwriting in High Risk Mortgage Markets."
- **Goodman-Bacon, Andrew.** 2021. "Difference-in-differences with variation in treatment timing." *Journal of Econometrics*, 225(2): 254–277.
- **Griffin, John M, and Alex Priest.** 2023. "Is COVID Revealing a Virus in CMBS 2.0?" *The Journal of Finance*, 78(4): 2233–2276.
- Gupta, Arpit, and Christopher Hansman. 2022. "Selection, leverage, and default in the mortgage market." *The Review of Financial Studies*, 35(2): 720–770.
- **Gupta, Arpit, Vrinda Mittal, Jonas Peeters, and Stijn Van Nieuwerburgh.** 2022. "Flattening the curve: pandemic-induced revaluation of urban real estate." *Journal of Financial Economics*, 146(2): 594–636.
- Hadland, Scott E, Ariadne Rivera-Aguirre, Brandon DL Marshall, and Magdalena Cerdá. 2019. "Association of pharmaceutical industry marketing of opioid products with mortality from opioid-related overdoses." *JAMA Network Open*, 2(1): e186007–e186007.
- Han, Lu. 2010. "The effects of price risk on housing demand: empirical evidence from US markets." *The Review of Financial Studies*, 23(11): 3889–3928.

- Harris, Matthew C, Lauren M Kessler, and Matthew N Murray. 2021. "Prescription opioids and labor market pains: The effect of Schedule II opioids on labor force participation and unemployment." *American Economic Journal: Economic Policy*, 13(1): 265–293.
- Holtermans, Rogier, Matthew E Kahn, and Nils Kok. 2022. "Climate risk and commercial mortgage delinquency." *Journal of Regional Science*.
- **Ivanich, Jerreed D, Julia Weckstein, Paul S Nestadt, Mary F Cwik, Melissa Walls, Emily E Haroz, Victoria M O'Keefe, Novalene Goklish, and Allison Barlow.** 2021. "Suicide and the opioid overdose crisis among American Indian and Alaska Natives: a storm on two fronts demanding swift action." *The American journal of drug and alcohol abuse*, 47(5): 527–534.
- Jansen, Mark. 2023. "Spillover effects of the opioid epidemic on consumer finance." *Journal of Financial and Quantitative Analysis*, 58(6): 2365–2386.
- Khan, Anam M, Paul Lin, Neil Kamdar, Elham Mahmoudi, Kenzie Latham-Mintus, Lindsay Kobayashi, and Philippa Clarke. 2024. "Location Matters: The Role of the Neighborhood Environment for Incident Cardiometabolic Disease in Adults Aging With Physical Disability." *American Journal of Health Promotion*, 38(5): 633–640.
- Koijen, Ralph SJ, and Stijn Van Nieuwerburgh. 2020. "Combining life and health insurance." *The Quarterly Journal of Economics*, 135(2): 913–958.
- Krueger, Alan B. 2017. "Where have all the workers gone? An inquiry into the decline of the US labor force participation rate." *Brookings Papers on Economic Activity*, 2017(2): 1–87.
- Liu, Crocker H, Chen Zheng, and Bing Zhu. 2022. "Does Putting All Your Eggs in One Basket Add Value? The Case of a Spatial Concentration of Same Industry Firms." Working Paper.
- Melendez, Robert, Finlay Jessica Clarke Philippa Noppert Grace Gypin Lindsay, and Ellis Dyke. 2024. "National Neighborhood Data Archive (NaNDA): Arts, Entertainment, and Leisure Establishments by Census Tract and ZCTA, United States, 1990-2021." Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor].
- **Ouimet, Paige, Elena Simintzi, and Kailei Ye.** 2023. "The impact of the opioid crisis on firm value and investment." *Available at SSRN 3338083*.
- **Parise, Gianpaolo, and Kim Peijnenburg.** 2019. "Noncognitive abilities and financial distress: evidence from a representative household panel." *The Review of Financial Studies*, 32(10): 3884–3919.
- Pearson, John, Cameron Jacobson, Nkemdirim Ugochukwu, Elliot Asare, Kelvin Kan, Nathan Pace, Jiuying Han, Neng Wan, Robert Schonberger, and Michael Andreae. 2023. "Geospatial analysis of patients' social determinants of health for health systems science and disparity research." *International anesthesiology clinics*, 61(1): 49–62.

- **Reid, Janet M, and Patricia D Sobczak.** 2022. "Review of Data Axle." *Journal of Business & Finance Librarianship*, 27(4): 310–313.
- **Serivice, Congressional Research.** 2020. "COVID-19 and the Future of Commercial Real Estate Finance."
- Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199.
- Yang, Tse-Chuan, Carla Shoff, Seulki Kim, and Benjamin A Shaw. 2022. "County social isolation and opioid use disorder among older adults: A longitudinal analysis of Medicare data, 2013–2018." *Social Science Medicine*, 301: 114971.

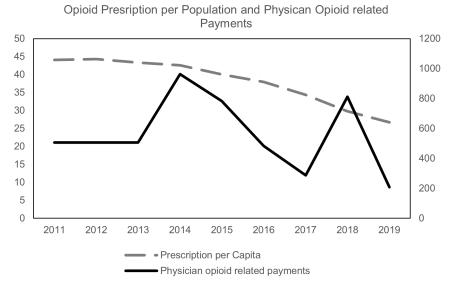


Figure 1: Opioid Abuse Proxies over Time

Note: This figure plots the evolution of annual opioid prescriptions per capita (dashed line) and physician opioid-related payments (solid line) from 2011 to 2019.

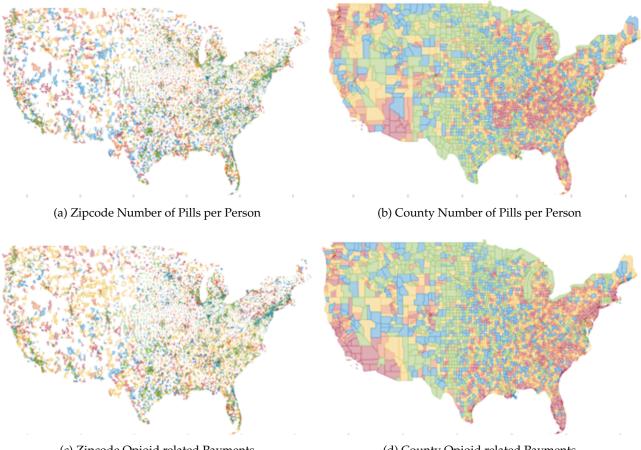


Figure 2: Opioid Abuse Proxies across the Nation

(c) Zipcode Opioid related Payments

(d) County Opioid related Payments

Note: Figure 2A presents the number of pills distributed per person at zipcode (Left) and County(Right) level. Figure 2B illustrates Pphysician Opioid related payments at the zipcode (Left) and County(Right) level. We classify these zip codes or counties into five quantiles, ranging from the 20% of zip codes with the lowest amount (Q1) to the 20% with the highest amount (Q5). The colors red, orange, yellow, blue, and green represent 20% of zip codes, with the highest (Q5) to the lowest (Q1).

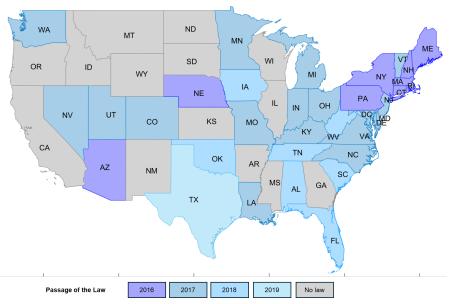
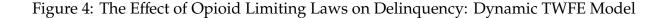
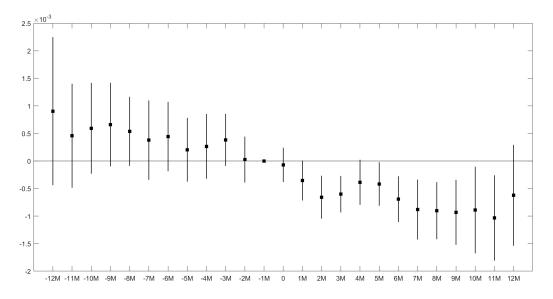


Figure 3: Passage of Opioid Limiting Laws by States

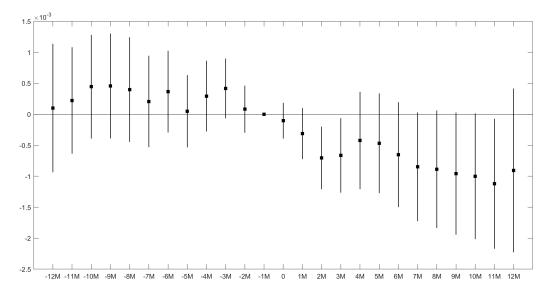
Note: This figure plots the geographical distribution of passage year of opioid limiting laws across states.





Note: this graph illustrates the coefficients and 95% confidence interval for the variable of the years before and after the in-force of Opioid limiting laws on the mortgage delinquency rate. Treated and non-treated states are matched using propensity score matching with the nearest neighbors method. Control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year. Standard errors are clustered at the property-year level.

Figure 5: The Effect of Opioid Limiting Laws on Delinquency: Interacted Weighted Dynamic TWFE Model



Note: this graph illustrates the coefficients and 95% confidence interval for the variable of the years before and after the in-force of Opioid limiting laws on the mortgage delinquency rate. Treated and non-treated states are matched using propensity score matching with the nearest neighbors method. Control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year. Standard errors are clustered at the property-year level.

	Mean	Std	25%	50%	75%
Panel A Mortgage Characteristics					
Delinquency_60 day (%)	0.280	5.280	0	0	0
Delinquency_90 day (%)	0.243	4.925	0	0	0
Delinquency_30 day (%)	0.356	5.952	0	0	0
NOI (1000 USD)	1999	4711	513	1066	2013
LTV	0.739	0.175	0.650	0.726	0.797
Occupancy	0.930	0.082	0.910	0.950	0.980
Loan Rate	0.045	0.010	0.040	0.045	0.049
Remaining Loan Term (month)	86	46	58	82	104
OverStatement	0.171	0.376	0	0	0
Interest only loan	0.087	0.281	0	0	0
Built before 1960	0.135	0.341	0	0	0
Built between 1960 and 1970	0.118	0.323	0	0	0
Built between 1970 and 1980	0.153	0.360	0	0	0
Built between 1980 and 1990	0.192	0.394	0	0	0
Built between 1990 and 2000	0.135	0.342	0	0	0
Built between 2000 and 2010	0.204	0.403	0	0	0
Panel B Zip-Code Characteristics					
Number of Pills per Capita	40	32	17	32	53
Number of Pills per Capita (MME)	50	43	20	39	66
Physician opioid related payments	9.53	113.48	0.06105	0.69605	2.93
Total Number of Physicians	75	124	13	36	90
Empolyment Employment	18084	18350	6838	13002	23145
Busisness Concentration	0.164	0.066	0.123	0.147	0.182
Population over 60	0.201	0.070	0.157	0.195	0.234
Poluation Population between 20 and 60	0.573	0.067	0.539	0.567	0.598
Sex Ratio	0.967	0.120	0.912	0.956	1.002
Disable Population	0.120	0.042	0.090	0.115	0.146
Population without insurance	0.149	0.105	0.074	0.128	0.201
Poluation Population working less than 17 weeks per year	0.073	0.068	0.002	0.095	0.126
Poluation Population below the poverty level	0.189	0.141	0.077	0.158	0.270
Median Rent to Income Ratio	0.306	0.053	0.274	0.301	0.336
Living Sales Volume (1000USD)	263	270	100	199	346
Dining Sales Volume (1000USD)	55	54	21	41	72
Home Related Expenses (1000USD)	101	114	26	67	139
Heathcare Amenities	118	125	30	84	168
Dining Amenities	64	55	25	54	91
Entertainment Amenities	32	28	13	27	45
Grocery Stores	23	23	9	19	32
Schools	16	12	7	14	23
Panel C County Characteristics					
Prescription Rate	0.802	0.362	0.554	0.763	1.000

Table 1: Summary Statistics

Note: The table present the summary statistics of mortgage-, zip-code- and county-level variables in our analysis.

	(1)	(2)	(3)
Dep. Var.	Delinquency	Opioid Pills	Delinquency
OP	0.0189***		0.0133***
	(0.0018)		(0.0018)
Physician Opi.Payment		0.0103***	
Emo	-0.0006***	(0.0013) 0.0157***	-0.0008***
Lino	(0.0001)	(0.0016)	(0.0001)
EmpConcen	-0.0015**	0.1377***	-0.0032***
	(0.0007)	(0.0160)	(0.0009)
Over60	-0.0123*** (0.0011)	0.0955*** (0.0258)	-0.0135*** (0.0012)
20-60	-0.0142***	-0.0750***	-0.0129***
	(0.0009)	(0.0248)	(0.0010)
Sex Ratio	0.0009**	0.0318***	0.0004
Disable	(0.0004)	(0.0097) 2.9422***	(0.0004)
Disable	0.0007 (0.0017)	(0.0377)	-0.0333** (0.0131)
No HealthInsur.	-0.0027***	-0.0550***	-0.0020***
	(0.0005)	(0.0115)	(0.0005)
Unempoly.	0.0097***	0.0446	0.0090***
Poverty Rate	(0.0013) 0.0040***	(0.0398) -0.2058***	(0.0013) 0.0064^{***}
Toverty Rate	(0.0040	(0.0108)	(0.0010)
Rent Cost	-0.0024**	-0.4239***	0.0022
-	(0.0010)	(0.0232)	(0.0022)
Total Physicians	-0.0003***	0.0392***	-0.0008***
LTV secur	(0.0000) 0.0412***	(0.0013) -0.2628***	(0.0002) 0.0413***
El V_beeur	(0.0004)	(0.0355)	(0.0004)
Loan Rate_secur	0.2549***	0.0112	0.2557***
-	(0.0063)	(0.0365)	(0.0063)
Term	-0.0017*** (0.0001)	0.2263*** (0.0294)	-0.0017*** (0.0001)
Overstatement	0.0078***	-0.0030	0.0078***
	(0.0001)	(0.0283)	(0.0001)
Interest Only	0.0044***	0.0016	0.0043***
	(0.0002)	(0.0290)	(0.0002)
Construction Year	Yes	Yes	Yes
Property Type	Yes	Yes	Yes
Deal Type State	Yes Yes	Yes Yes	Yes Yes
Year_month	Yes	Yes	Yes
No. of obs	1,630,069	69,108	1,630,069
R2	0.0330	0.2879	0.0329

Table 2: The Impact of Opioid Abuse on Mortgage Delinquency

Note: Column 1 reports the results of linear probit model with over 60 day delinquency as the dependent variable and opioid pill distribution per 100 population as the key variable. Columns 2 and 3 report a two stage linear probit model with the number of primary physicians per capita as the instrument. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. In Column 1, standard errors are clustered at the property-year level. In Columns 2 and 3, the standard errors are based on wild bootstrapping.

Dep. Var.	(1)	(2)
=Delinquency	90 day	30 day
OP	0.0112***	0.0103***
	(0.0016)	(0.0022)
Controls	Yes	Yes
Const. Year	Yes	Yes
Property Type	Yes	Yes
Deal Type	Yes	Yes
State	Yes	Yes
Year_month	Yes	Yes
No. of obs	1,630,069	1,630,069
R^2	0.0331	0.0306

Table 3: Robustness Tests: Alternative Measurement for Delinquency

Note: This table reports the results of linear probit model with over 90 delinquency (Column 1) and over 30 day delinquency (Column 2) as the dependent variable and the instrumented opioid pills per 100 population as the key variable. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

Dep. Var.	(1)	(2)	(3)	(4)	(5)
= Delinquency	MME	Lagged Opioid	Lagged Opioid	1km Ring	3km Ring
OP_MME	0.0069***				
	(0.0009)				
OP_lag1		0.0213***			
		(0.0024)			
OP_lag2			0.0409***		
			(0.0037)		
OP_1km				0.0005***	
				(0.0001)	
OP_3km					0.0002
					(0.0002)
Controls	Yes	Yes	Yes	Yes	Yes
Const. Year	Yes	Yes	Yes	Yes	Yes
Property Type	Yes	Yes	Yes	Yes	Yes
Deal Type	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes
Year_month	Yes	Yes	Yes	Yes	Yes
No. of obs	1,630,069	1,578,236	1,393,200	755,714	866,094
R2	0.0329	0.0336	0.0387	0.0131	0.0113

Table 4: Robustness Tests: Alternative Measurement for Opioid Abuse

Note: This table reports the results of linear probit model with over 60 day delinquency as the dependent variable and the instrumented opioid pills per 100 population as the key variable. Column 1 uses the Morphine Milligram Equivalent adjusted prescription rate. Columns 2 and 3 report the results based on one and two year lag of the prescription rate. Columns 4 and 5 report the results based on the prescription rate in the range within 1km and 3km from the property. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

	(1)	(2)	(3)
Dep. Var.	Delinquency	Opioid Prescription	Delinquency
Prescription	0.0052***		0.0046***
	(0.0006)		(0.0004)
OP		0.1018***	
		(0.0079)	
Controls	Yes	Yes	Yes
Const. Year	Yes	-	Yes
Property Type	Yes	-	Yes
Deal Type	Yes	-	Yes
State	Yes	Yes	Yes
Year_month	Yes	-	Yes
Year	-	Yes	-
No. of obs	940,670	7,668	940,670
R2	0.0314	0.5818	0.0312
F		442.09***	

Table 5: Robustness Tests: Alternative Instrument for Opioid Abuse

Note: This table reports the results of linear probit model with over 60 day delinquency as the dependent variable and the instrumented opioid prescription per 100 population as the key variable. Columns 2 and 3 report the results based on two stage linear probit model. Control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

Dep. Var =Delinquency	(1) Full Sample	(2) Matched Sample
Post_Law	-0.0019** (0.0009)	-0.0009*** (0.0003)
Controls	Yes	Yes
Construction Year	Yes	Yes
Property Type	Yes	Yes
Deal Type	Yes	Yes
State	Yes	Yes
Year	Yes	Yes
No. of obs	1,630,069	1,124,353
R2	0.0330	0.0123

Table 6: Impact of Opioid Limiting Laws on Mortgage Delinquency

Note: This table reports the results of the linear probit model with over 60 day delinquency as the dependent variable and the passage of Opioid limiting laws as the key variable. Column 1 is based on all loans, and Column 2 is based on loans in the matched states using the propensity score matching with three nearest neighbors methods. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the state level.

	(1)	(2)
Dep. Var.	ΔΝΟΙ	$\Delta Occupancy$
OP	-0.2737***	-0.1574***
	(0.0198)	(0.0544)
Emp	0.0045***	0.0042
-	(0.0004)	(0.0044)
EmpConcen	0.0157***	-0.0089
-	(0.0045)	(0.0448)
Over60	0.0251***	-0.0427
	(0.0057)	(0.0560)
20-60	-0.1117***	-0.0587
	(0.0045)	(0.0444)
Sex Ratio	0.0286***	0.0078
	(0.0021)	(0.0205)
Disable	0.6519***	0.5030
	(0.0627)	(0.6205)
No HealthInsur.	-0.0014	-0.0016
	(0.0025)	(0.0246)
Unempoly.	-0.0314***	-0.1265**
	(0.0061)	(0.0597)
Poverty Rate	-0.0367***	-0.0915*
-	(0.0048)	(0.0473)
Rent Cost	-0.0366***	-0.0660
	(0.0103)	(0.1023)
Total Physicians	0.0128***	0.0081
	(0.0010)	(0.0100)
Property Type	Yes	Yes
Deal Type	Yes	Yes
State	Yes	Yes
Year_month	Yes	Yes
No. of obs	1,629,325	1,555,064
R2	0.3521	0.0006

Table 7: Channel Analysis: Change in NOI and Occupancy Rate

Note: The table reports the impact of instrumented opioid pills per 100 population on change in NOI and occupancy since securitization. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median earning and median rent. We also include the dummy variables for property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

	Panel	l A: Sales of I	Local Retail S	ector		
Dep. Var. = Log(Sale Volume per Store) Category	(1) Grocery	(2) Other Essential Basic	(3) Home & Furniture	(4) Other Consumer Goods	(5) Dining	(6) Alcoholic Beverages
OP	0.2875 (0.2709)	-0.1747 (0.1866)	-0.8911*** (0.2706)	-0.7463*** (0.2379)	-0.5748*** (0.1383)	-0.1817 (0.2849)
Controls County× <i>Year</i> No. of obs R2 IV Coef	Yes Yes 69,041 0.2799 0.0110*** (0.0012)	Yes Yes 69,000 0.2186 0.0110*** (0.0012)	Yes Yes 69,024 0.1253 0.0109*** (0.0012)	Yes 69,064 0.2663 0.0109*** (0.0012)	Yes Yes 69,090 0.2691 0.0108*** (0.0012)	Yes Yes 55,713 0.3494 0.0111*** (0.0013)
	Panel B:	Neighborho	od Amenity	Density		
Dep. Var. = Log(Counts per 1000 Pop.) Category	(1) Healthcare	(2) Dinning	(3) Leisure	(4) Grocery	(5) Retail	(6) Schools
OP	-0.1794 (0.2770)	-1.4038*** (0.3168)	-0.9871*** (0.2259)	-0.6197*** (0.1666)	-0.8981*** (0.2562)	-0.7669*** (0.1696)
Controls County× <i>Year</i> No. of obs R2 IV Coef	Yes Yes 53,620 0.8329 0.0082*** (0.0014)	Yes Yes 53,620 0.3963 0.0082*** (0.0014)	Yes Yes 53,620 0.4617 0.0082*** (0.0014)	Yes Yes 53,620 0.5208 0.0082*** (0.0014)	Yes Yes 53,620 0.3353 0.0082*** (0.0014)	Yes Yes 53,620 0.1155 0.0082*** (0.0014)

Table 8: Channel Analysis:Local Economic Conditions and Opioid Abuse

Note: The table reports the impact of the instrumented opioid pills per 100 population on the sales volume of local retail sectors (Panel A) and neighborhood amenity density (Panel B). In Panel A, Retail sector includes grocery stores (Column 1), stores for other essential goods (Column 2), home and furniture stores (Column 3), retail stores for other consumer goods (Column 4), eating places (Column 5), and drinking places (Column 6). In Panel B, local amenities include healthcare amenities (Column 1), dinning amenities (Column2), entertainment amenities (Column3), Grocery Stores (Column4), Other Retail Stores (Column5) and Schools (Column6). Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, and total number of physicians. County by year fixed effects are included. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)		
Dep. Var.	ΔNOI	$\Delta Occupancy$	Delinquency		
Panel A: Sales of Local Retail Sector					
Log(Retail Sale)	0.0031***	0.0108*	-0.0006***		
0	(0.0007)	(0.0066)	(0.0001)		
Controls	Yes	Yes	Yes		
Construction Year	No	No	Yes		
Property Type	No	No	Yes		
Deal Type	Yes	Yes	Yes		
State	Yes	Yes	Yes		
Year_month	Yes	Yes	Yes		
No. of obs	1,391,347	1,327,916	1,392,028		
R2	0.3624	0.0005	0.0341		
Panel B: N	Veighborhoo	od Amenity Der	nsity		
Log(Amenities)	0.0020***	0.0063	-0.0006***		
	(0.0005)	(0.0046)	(0.0001)		
Controls	Yes	Yes	Yes		
Construction Year	No	No	Yes		
Property Type	No	No	Yes		
Deal Type	Yes	Yes	Yes		
State	Yes	Yes	Yes		
Year_month	Yes	Yes	Yes		
No. of obs	925,164	865,325	925,164		
R2	0.3181	0.0007	0.0390		

Table 9: Channel Analysis: Local Econnomic Conditions and Loan Performance

Note: The table reports the impact of local retail sale (Panel A) and amenity density (Panel B) on change in NOI since securitization (Column 1), change in occupancy since securitization (Column 2) and 60 day delinquency (Column 3). Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, and total number of physicians. In Column 3, property level characteristics are also controlled, including loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization and a dummy variable for interest only loan. We also include the dummy variables for property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Dep. Var. = Delinquency				
	(1)	(2)	(3)	(4)	
Туре	Residential	Retail	Office	Other	
OP	0.0252***	0.0159***	0.0034	-0.0103	
	(0.0019)	(0.0057)	(0.0067)	(0.0111)	
Controls	Yes	Yes	Yes	Yes	
Construction Year	Yes	Yes	Yes	Yes	
Property Type	No	No	No	Yes	
Deal Type	Yes	Yes	Yes	Yes	
State	Yes	Yes	Yes	Yes	
Year_month	Yes	Yes	Yes	Yes	
No. of obs	1,133,975	252,750	104,133	132,364	
R^2	0.0544	0.0169	0.0262	0.0682	

Table 10: Heterogeneity: Role of Property Types

Note: The table reports the impact of the instrumented opioid pills per 100 population on mortgage over 60 day delinquency. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

Dep. Var.				
= Delinquency	(1)	(2)	(3)	(4)
OP	0.0127***	0.0161***	0.0110***	0.0180***
	(0.0021)	(0.0026)	(0.0022)	(0.0020)
OP ×Noinsurance	0.0036***	(()	(, , , , , , , , , , , , , , , , , , ,
	(0.0010)			
Noinsurance	-0.0032***			
	(0.0010)			
$OP \times Emp$		-0.0002**		
,		(0.0001)		
Emp		-0.0007***		
1		(0.0001)		
OP × <i>RentalCost</i>		× ,	0.0102***	
			(0.0034)	
Rental Cost			-0.0022	
			(0.0029)	
OP ×NonAgency				-0.0059***
				(0.0002)
NonAgency				0.0031***
				(0.0002)
Controls	Yes	Yes	Yes	Yes
Construction Year	Yes	Yes	Yes	Yes
Property Type	Yes	Yes	Yes	Yes
Deal Type	Yes	Yes	Yes	No
State	Yes	Yes	Yes	Yes
Year_month	Yes	Yes	Yes	Yes
No. of obs	1,630,069	1,630,069	1,621,244	1,630,069
R2	0.0329	0.0329	0.0330	0.0325

Table 11: Heterogeneity: Role of Local Economic Conditions and Loan Characteristics

Note: The table reports the impact of the instrumented opioid pills per 100 population on mortgage over 60 day delinquency. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

Dep. var.= Delinquency(1)(2)(3)OP 0.0082^{***} 0.0113^{**} 0.0225^{***} (0.0016) (0.0019) (0.0018) OP ×Black 0.0021^{***} (0.0001) OP ×Asian 0.0260^{***} (0.0019) OP ×Other 0.0003 (0.0017) Black -0.0021^{***} (0.0017) Black -0.0021^{***} (0.0013) Other 0.0065^{***} (0.0013) Other -0.0044^{***} (0.0013) Other 0.0146^{***} (0.0020) Age15_24 0.0146^{***} (0.0008) Demo -0.00175^{***} (0.0008) Demo -0.0175^{***} (0.0018) ControlsYesYesYesYesYesProperty TypeYesYesDeal TypeYesYesYear_monthYesYesYear_monthYesYesNo. of obs $1,630,069$ $1,630,069$ $1,630,069$ $1,630,069$ $1,043,493$ R2 0.0329 0.0328 0.0479	Dere Ver			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Dep. Var.	(1)	(2)	(2)
$\begin{array}{c ccccc} (0.0016) & (0.0019) & (0.0018) \\ OP \times Black & 0.0021^{***} & & \\ & (0.0001) & & \\ OP \times Asian & 0.0260^{***} & & \\ & (0.0019) & & \\ OP \times Other & 0.0003 & & \\ & & (0.0017) & \\ Black & -0.0021^{***} & & \\ & & (0.0003) & & \\ Asian & -0.0065^{***} & & \\ & & (0.0013) & & \\ Other & -0.0044^{***} & & \\ & & (0.0013) & & \\ Other & -0.0044^{***} & & \\ & & (0.0020) & \\ Age15_24 & 0.0146^{***} & & \\ & & (0.0020) & \\ Age15_24 & -0.0016 & & \\ & & & (0.0020) & \\ Age15_24 & -0.0016 & & \\ & & & & (0.0008) & \\ OP \times Demo & & & -0.0049^{***} & \\ & & & & & (0.0008) & \\ Demo & & & & -0.0175^{***} & \\ & & & & & & (0.0018) & \\ OP \times Demo & & & & & -0.0175^{***} & \\ & & & & & & & & \\ OOD(17) & & & & & & & \\ Property Type & Yes & Yes & Yes & \\ Property Ty$	= Delinquency	(1)	(2)	
OP ×Black 0.0021^{***} (0.0001) OP ×Asian 0.0260*** (0.0019) OP ×Other 0.0003 (0.0017) Black -0.0021^{***} (0.0003) Asian -0.0065^{***} (0.0013) Other -0.0044^{***} (0.0013) Other -0.0044^{***} (0.0013) OP ×Age15_24 0.0146^{***} (0.0020) Age15_24 -0.0016 (0.0014) 00008 Demo -0.0049^{***} (0.0008) -0.0175^{***} (0.0008) 0.0014 OP ×Demo -0.0016 (0.0018) 0.0017 Demo -0.0175^{***} (0.0018) 0.0018 Demo -0.0175^{***} (0.0018) 0.0018 Demo -0.0175^{***} (0.0018) 0.0018 Demo Yes Yes Property Type Yes Yes Property Type Yes	OP	0.0082***	0.0113**	0.0225***
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.0016)	(0.0019)	(0.0018)
OP \times Asian 0.0260*** (0.0019) 0 OP \times Other 0.0003 (0.0017) 1 Black -0.0021*** (0.0003) - Asian -0.0065*** (0.0013) - Other -0.0044*** (0.0013) - Other -0.0044*** (0.0020) - Age15_24 0.0146*** (0.0020) - Age15_24 -0.0016 (0.0013) - OP \times Demo -0.0049*** (0.0008) - Demo -0.0175*** (0.0018) - Or \times Demo -0.0175*** (0.0018) - Oemo -0.0175*** (0.0018) - Demo -0.0175*** (0.0018) - Demo -0.0175*** (0.0018) - Demo - State Yes Property Type Yes Yes Pres Yes	$OP \times Black$	0.0021***		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		· · /		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	OP ×Asian			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$				
Black -0.0021^{***} (0.0003) (0.0003) Asian -0.0065^{***} (0.0013) (0.0013) Other -0.0044^{***} (0.0013) (0.0020) OP $\times Age15_24$ 0.0146^{***} (0.0020) (0.0020) Age15_24 -0.0016 (0.0014) (0.0049^{***}) (0.0008)OP $\times Demo$ -0.0049^{***} (0.0008)Demo -0.00175^{***} (0.0018)ControlsYesYesYesProperty TypeYesYesYesProperty TypeYesYesYesStateYesYear_monthYesYear_monthYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYesYesYear_monthYesYearYesYearYesYearYesYearYesYearYesYearYesYearYesYearYesYearYearYearYearYearYearYearYearYearYearY	$OP \times Other$			
Asian -0.0065^{***} (0.0013) (0.0013) Other -0.0044^{***} (0.0013) $(0.0146^{***}$ (0.0020)OP $\times Age15_24$ 0.0146^{***} (0.0020)Age15_24 -0.0016 (0.0014)OP $\times Demo$ -0.0049^{***} (0.0008)Demo -0.0049^{***} (0.0018)ControlsYes Yes Yes (0.0018)ControlsYes <br< td=""><td></td><td>· ,</td><td></td><td></td></br<>		· ,		
Asian -0.0065*** (0.0013) Other -0.0044*** (0.0013) OP $\times Age15_24$ 0.0146*** (0.0020) Age15_24 -0.0016 (0.0014) (0.0014) OP $\times Demo$ -0.0049*** (0.0008) -0.0175*** Demo -0.0175*** (0.0018) (0.0018) Demo -0.0175*** (0.0018) -0.0175*** Demo -0.0175*** (0.0018) -0.0175*** Demo -0.0175*** (0.0018) -0.0175*** No. of obs 1,630,069 1,630,069	Black	-0.0021***		
(0.0013) $-0.0044***$ (0.0013) (0.0013) OP ×Age15_24 0.0146^{***} (0.0020) Age15_24 -0.0016 (0.0014) OP ×Demo -0.0049^{***} (0.0008) Demo -0.0049^{***} (0.0018) ControlsYes Yes Yes YesControlsYes Ye		(/		
Other-0.0044*** (0.0013) $OP \times Age15_24$ 0.0146^{***} (0.0020)Age15_24 -0.0016 (0.0014) $OP \times Demo$ -0.0049^{***} (0.008) $Demo$ -0.0175^{***} (0.0018)ControlsYesYesYesProperty TypeYesYesYesProperty TypeYesYesYesStateYesYear_monthYesYear_monthYesYear_monthYesYeasYesYeasYesYear_monthYesYeasYeasYeas <t< td=""><td>Asian</td><td>-0.0065***</td><td></td><td></td></t<>	Asian	-0.0065***		
(0.0013) (0.0013) $OP \times Age15_24$ 0.0146^{***} (0.0020) (0.0020) Age15_24 -0.0016 (0.0014) (0.0014) $OP \times Demo$ -0.0049^{***} $OP \times Demo$ -0.0049^{***} (0.0008) -0.0175^{***} $Demo$ -0.0175^{***} $Demo$ -0.0175^{***} (0.0018) -0.0175^{***} $Demo$ Yes Yes Yes $Semo$ Yes $Semo$ Yes $Semo$ Yes $Semo$ Yes $Semo$ Yes <		· · /		
OP $\times Age15_24$ 0.0146*** (0.0020) Age15_24 -0.0016 (0.0014) (0.0019) OP $\times Demo$ -0.0049*** Demo -0.0175*** (0.0018) (0.0018) Controls Yes Yes Controls Yes Yes Property Type Yes Yes Property Type Yes Yes State Yes Yes Year_month Yes Yes No. of obs 1,630,069 1,630,069 1,043,493	Other			
Age15_24 (0.0020) Age15_24 -0.0016 (0.0014) -0.0049*** OP ×Demo -0.0049*** Demo -0.0175*** (0.0008) -0.0175*** Demo -0.0175*** (0.0018) (0.0018) Controls Yes Yes Property Type Yes Yes Peal Type Yes Yes State Yes Yes Year_month Yes Yes No. of obs 1,630,069 1,630,069 1,043,493		(0.0013)		
Age15_24 -0.0016 (0.0014)OP ×Demo -0.0049^{***} (0.0008)Demo -0.0175^{***} (0.0018)ControlsYesYesYesConstruction YearYesProperty TypeYesYesYesProperty TypeYesYesYesStateYesYear_monthYesYear_monthYes1,630,0691,630,0691,630,0691,043,493	$OP \times Age15_24$			
OP ×Demo -0.0049*** OP ×Demo -0.0049*** Demo -0.0175*** OP ×Demo -0.0175*** Controls Yes Yes Controls Yes Yes Property Type Yes Yes Property Type Yes Yes State Yes Yes Year_month Yes Yes No. of obs 1,630,069 1,630,069 1,043,493			· · ·	
$\begin{array}{cccc} OP \times Demo & -0.0049^{***} & & & & & & & & & & & & & & & & & &$	Age15_24			
Demo(0.0008) -0.0175*** (0.0018)ControlsYesYesConstruction YearYesYesProperty TypeYesYesDeal TypeYesYesStateYesYesYear_monthYesYesNo. of obs1,630,0691,630,0691,043,493			(0.0014)	
Demo-0.0175*** (0.0018)ControlsYesYesConstruction YearYesYesProperty TypeYesYesProperty TypeYesYesDeal TypeYesYesStateYesYesYear_monthYesYesNo. of obs1,630,0691,630,069	OP ×Demo			
ControlsYesYesYesConstruction YearYesYesYesProperty TypeYesYesYesDeal TypeYesYesYesStateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493				· · · ·
ControlsYesYesYesConstruction YearYesYesYesProperty TypeYesYesYesDeal TypeYesYesYesStateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493	Demo			
Construction YearYesYesYesProperty TypeYesYesYesDeal TypeYesYesYesStateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493				(0.0018)
Property TypeYesYesYesDeal TypeYesYesYesStateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493	Controls	Yes	Yes	Yes
Deal TypeYesYesYesStateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493	Construction Year	Yes	Yes	Yes
Deal TypeYesYesYesStateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493	Property Type	Yes	Yes	Yes
StateYesYesYesYear_monthYesYesYesNo. of obs1,630,0691,630,0691,043,493	1 7 71	Yes	Yes	Yes
No. of obs 1,630,069 1,630,069 1,043,493	State	Yes	Yes	Yes
	Year_month	Yes	Yes	Yes
R2 0.0329 0.0328 0.0479	No. of obs	1,630,069	1,630,069	1,043,493
	R2	0.0329	0.0328	0.0479

 Table 12: Heterogeneity: Role of Local Demographic and Political Conditions

Note: The table reports the impact of the instrumented opioid pills per 100 population on mortgage over 60 day delinquency. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

	(1)	(2)	(3)
. Var.	Initial Spread	LTV	DSCR
OP	0.7749***	-0.0834**	2.4133**
	(0.1882)	(0.0410)	(0.9638)
Emp	-0.0486***	-0.0011	0.0446
1	(0.0085)	(0.0015)	(0.0364)
EmpConcen	-0.2730***	0.0055	-0.5201
1	(0.0863)	(0.0156)	(0.3701)
Over60	-0.2909***	-0.1297***	-1.0487**
	(0.1046)	(0.0189)	(0.4485)
20-60	-0.2693***	-0.1509***	-1.1915***
	(0.0879)	(0.0158)	(0.3768)
Sex Ratio	-0.0376	0.0036	-0.1591
	(0.0356)	(0.0064)	(0.1527)
Disable	-1.6626	0.3846*	-5.5941
	(1.1537)	(0.2084)	(4.9480)
No HealthInsur.	0.0380	-0.0202**	-0.0762
	(0.0458)	(0.0083)	(0.1966)
Unempoly.	0.0630	0.0842***	0.1431
1 5	(0.1511)	(0.0273)	(0.6478)
Poverty Rate	0.3429***	-0.0269*	0.3986
5	(0.0886)	(0.0160)	(0.3799)
Rent Cost	0.0051***	-0.0004	0.0050
	(0.0019)	(0.0004)	(0.0083)
Total Physicians	-0.0427**	0.0058*	-0.1013
,	(0.0189)	(0.0034)	(0.0810)
Spread_secur	· · · · · ·	0.0025*	-0.4572***
1		(0.0013)	(0.0298)
LTV_secur	0.0789**		-10.6743***
	(0.0399)		(0.1319)
DSRC_secur	-0.0260***	-0.0190***	· · · ·
_	(0.0017)	(0.0002)	
Term	0.0034***	-0.0004***	-0.0068***
	(0.0001)	(0.0000)	(0.0006)
Overstatement	0.2064***	-0.0234***	-0.0651
	(0.0359)	(0.0065)	(0.1542)
Interest Only	-0.2493***	-0.0589***	-0.1146***
5	(0.0130)	(0.0023)	(0.0557)
Construction Year	Yes	Yes	Yes
Property Type	Yes	Yes	Yes
Deal Type	Yes	Yes	Yes
State	Yes	Yes	Yes
Year_month	Yes	Yes	Yes
No. of obs	20,163	20,163	20,163
R2	0.5543	0.5405	0.2907

Table 13: Loan Rate and Covenant

Note: The table (Column 1, 2 and 3) reports the impact of instrumented opioid pills per 100 population on the spread, loan-to-value ratio, and debt service coverage ratio at securitization, estimated using seemingly unrelated regressions to simultaneously model the three equations. Column 4 reports the impact of instrumented opioid pills per 100 population on deal level AAA subordination at deal securitization. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

Internet Appendix

Panel A Distribution by Year		
Year	# Mortgage Securitization	
2011	1811	
2012	2583	
2013	3737	
2014	4424	
2015	5308	
2016	5638	
2017	6596	
2018	5237	

Table A1: Distribution of Mortgage

Panel B Distribution by Property Type

Property Type	# Mortgage	% Mortgage
СН	652	1.80%
HC	1	0.00%
IN	513	1.50%
LO	1695	4.80%
MF	24399	69.10%
MH	817	2.30%
MU	594	1.70%
OF	1892	5.40%
OT	51	0.10%
RT	4003	11.30%
SS	716	2.00%

Note: The table reports the distribution of mortgages by year Panel A) and property typePanel B) in our sample.

	(1)	(2)	(3)
Dep. Var. = Delinquency			
OP	0.0197***	0.0096***	0.0103***
	(0.0021)	(0.0010)	(0.0010)
Emp	-0.0006***	-0.0006***	-0.0004***
-	(0.0001)	(0.0001)	(0.0001)
EmpConcen	-0.0016**	-0.0015**	-0.001
1	(0.0006)	(0.0007)	(0.0007)
Over 60	-0.0124***	-0.0106***	-0.0105***
	(0.0012)	(0.0011)	(0.0011)
20-60	-0.0142***	-0.0121***	-0.0137***
	(0.0009)	(0.0009)	(0.0009)
Sex Ratio	0.0009**	0.0006	0.0012***
	(0.0004)	(0.0004)	(0.0004)
Disable	0.0014	0.0042**	0.0045**
Disable	(0.0014)	(0.0012)	(0.0019)
No health Insurance	-0.0027***	-0.0048***	-0.0030***
No nearm insurance	(0.0004)	(0.0048)	
Unomployed	0.0094***	0.0083***	(0.0005) 0.0088***
Unemployed			
	(0.0014)	(0.0012)	(0.0012)
Poverty Rate	0.0040***	0.0031***	0.0038***
	(0.0005)	(0.0004)	(0.0004)
Rent	0.0003	0.0000	0.0006**
-	(0.0003)	(0.0002)	(0.0002)
Total Physicians	-0.0003***	-0.0003***	-0.0003***
	(0.0001)	(0.0000)	(0.0000)
LTV_secur	0.0412***	0.0400***	0.0377***
	(0.0009)	(0.0004)	(0.0004)
Loan Rate_secur	0.2552***	0.2567***	0.2484***
	(0.0067)	(0.0063)	(0.0063)
Term	-0.0016***	-0.0016***	-0.0016***
	(0.0001)	(0.0001)	(0.0001)
OverStatement	0.0078***	0.0078***	0.0083***
	(0.0002)	(0.0001)	(0.0001)
Interest Only	0.0043***	0.0041***	0.0040***
	(0.0002)	(0.0002)	(0.0002)
Construction Year	Yes	Yes	Yes
Property Type	Yes	Yes	No
Deal Type	Yes	Yes	Yes
State	Yes	No	Yes
Year_month	Yes	No	No
State X Year	No	Yes	No
Property Type X Year	No	No	Yes
No. of obs	1,630,069	1,630,069	1,630,069
R2	700.033	0.0374	0.0327
- `		0.007 -	0.0021

Table A2: Fixed Effects Tests

Note: This table presents a robustness check of the main analysis by including various fixed effects in the specification.

	(1)	(2)
Dep. Var.	Initial Spread	Below AAA
OP	0.8706***	0.1006***
	(0.0607)	(0.0396)
Emp	-0.1613**	0.0223*
	(0.0777)	(0.0126)
EmpConcen	-0.6473	0.2572**
	(0.7286)	(0.1134)
Over60	2.6413**	-0.2977
	(1.3400)	(0.2068)
20-60	-2.0495*	-0.2999*
	(1.0681)	(0.1606)
Sex Ratio	-0.3172	-0.0474
	(0.3633)	(0.0502)
Disable	-0.0250	-0.0031
NT TT 1/1 T	(0.0305)	(0.0042)
No HealthInsur.	0.4321	-0.0937
TT 1	(0.6268)	(0.1066)
Unempoly.	3.6343**	-0.1497
Descentes Data	(1.8111) 1.0921**	(0.2301) -0.2370***
Poverty Rate	(0.5372)	
Rent Cost	0.0014	(0.0796) 0.0006
Kent Cost	(0.0151)	(0.0025)
Total Physicans	-0.1625***	-0.0226***
Total T Hysicalis	(0.0556)	(0.0086)
LTV_secur	-0.0653	0.6503***
	(0.3811)	(0.0751)
DSRC_secur	0.0009	-0.0089**
20110_000al	(0.0095)	(0.0043)
Term	-0.2579***	0.0116
	(0.0721)	(0.0182)
Overstatement	0.3926	0.0756
	(0.3385)	(0.1665)
Interest Only	-0.2415**	0.0582***
5	(0.0939)	(0.0182)
Deal Size	-0.3581***	-0.0191**
	(0.0341)	(0.0094)
Construction Year Share	Yes	Yes
Property Type Share	Yes	Yes
Deal Type	Yes	Yes
Year_month	Yes	Yes
No. of obs	915	470
R2	0.5587	0.7642

Table A3: Deal level pricing

Note: Note: The table reports the impact of instrumented opioid pills per 100 population on the weighted average coupon and AAA subordination level at the deal secularization. Other control variables include Zipcode level employment number, business concentration (HHI of sectoral employment), zipcode level percentage of the disabled population, percentage of the population without health insurance, percentage of the population working less than 13 weeks per year, percentage of population below the poverty rate, median rent to income ratio, total number of physicians, as well as property-level loan to value ratio at securitization, loan rate, loan term, income overstatement at securitization, and a dummy variable for interest only loan. We also include the dummy variables for the construction year group, property type, state, deal type, and year month. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are based on wild bootstrapping.

Figure A1: GIS Mapping of Neighborhoods

Note: This figure presents an example of a building locating near or at the border of a zip code. We define the neighborhood of a building as a 1km or 3km radius surrounding it using GIS.

