The Opioid Epidemic and Mortgage Lending: Credit or Demand Shock?

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Abstract

Local mortgage credit access and availability is reduced in areas with higher rates of opioid abuse. Among depository institutions, lenders' response to the opioid epidemic differs depending on their size and business model. Small banks are more likely to treat the opioid epidemic as a *negative demand shock*, while large banks are more likely to treat it as a *credit risk shock*. Locally, both small and large banks reduce mortgage lending volume in areas more affected by the opioid epidemic. On a national scale, only small banks experience a reduction origination volume due to exposure to the opioid epidemic, while large banks simply shift lending towards less exposed markets. Large banks are more likely to pass on the risks associated with opioid abuse to borrowers in terms of higher interest rates, raising annual mortgage interest rate payments by roughly $1.25 billion between 2007 and 2015.

Keywords: opioid epidemic, mortgages, financial intermediation, banking, risk management

JEL Codes: G21, H31, I15, R31

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1 Introduction

Since 2020, the public health crisis *du jour* in terms of media and academic attention has been COVID-19. However, only a few years prior, the opioid epidemic dominated public headlines in the US, which from 1999 to 2019 had taken the lives of over half a million people.[1] Though the opioid epidemic has dropped out of the recent news cycle, it has continued growing even as the COVID-19 pandemic has begun to subside. In 2021, over 107,000 people died from opioid overdoses, a 15% increase from the previous year.[2] The scale of the economic damage caused by the opioid epidemic is a growing interest in economic research, as the impact of what Case and Deaton (2015) popularized as "deaths of despair" has significant implications on how societal trends can spillover into financial markets and affect even households that were spared the direct effects of the epidemic.

Most of the financial literature treats the opioid epidemic as simply a credit risk shock for lenders. (Cornaggia et al., 2021, Jansen, 2022, and Agarwal, Li, et al., 2022) However, it is also possible that the opioid epidemic may function as a negative demand shock for financial services. Arteaga and Barone, 2022, Aliprantis, Fee, and Schweitzer, 2019, M. Harris et al., 2019 Ouimet, Simintzi, and Ye, 2020 find significant negative impacts by the opioid epidemic on labor force participation and productivity, which as Custodio, Cvijanovic, and Wiedemann, 2022 argues in turn may lead lower household income, thereby lowering demand for mortgage services. Thus, as opioid abuse increases in an area, a lender's borrower pool may decrease as potential borrowers exit the lending market, due to loss of income, incapacity or even death due to opioid abuse. Such negative demand shocks would not necessarily be incompatible with previous studies that treat opioid abuse as credit risk for lenders, as communities with higher rates of opioid abuse can experience a reduction both in the number of borrowers and the credit-worthiness of remaining borrowers.

Furthermore, differences in terms of business models and geographic reach may affect

[1] As of the end of 2019.

[2] Source: https://www.reuters.com/world/us/biden-announce-15-billion-fight-us-opioid-crisis-2022-09-23/

the nature of opioids' impact on bank lending behavior. Smaller, geographically constrained banks are more likely to react the opioid epidemic as a negative demand shock, meaning they are less able to shift lending away from exposed areas, and are forced to lend in areas where a greater proportion of potential borrowers are abusing opioids. However, larger banks with greater geographic diversity are more likely to treat opioid abuse as a credit risk shock, and thus not only are able to shift mortgage origination volume away from exposed markets, but also are more able to pass on the higher costs of opioid abuse onto their customers.

In this paper, using the U.S. mortgage market from 2006 to 2015, I find evidence in support of my hypothesis that lenders experienced the opioid epidemic both as a demand shock and a credit risk shock, and that the impact of the opioid epidemic depends on the size and geographic reach of the lender. First, using both Purdue Pharmaceutical's Oxycotin marketing efforts before the opioid epidemic, and Medicaid Part-D eligibility rates as instruments for local opioid supply, I find that both small and large banks significantly reduced local origination volume in areas with higher rates of opioid abuse. However, the impact of opioid abuse on reducing such lending volume was more than twice as large for large banks than for small banks. Second, I find that total geographic exposure to the opioid epidemic (as measured by bank branch location) has a negative impact on total nationwide origination volume only for small banks, while having no such negative impact for large banks. Taken together, these two results suggest that large banks are more able than small banks to shift mortgage lending activity away from areas that have been heavily impacted by the opioid epidemic.

Third, I examine the relationship between local opioid abuse and the approval rates of mortgage applications for bank lenders to determine if the reduction in lending volume is driven by reduced borrower demand, or by lenders reducing credit access due to higher credit risk. I find a significant negative relationship between approval rates and local opioid supply for large banks, but not for small banks, suggesting that the reduction in lending volume is driven by reduced credit supply for large banks, but also by reduced credit demand for small banks.

Fourth, I examine whether lenders price in the risk of opioid abuse into mortgage interest rates charged to borrowers. I find that for both purchase and refinancing mortgages, greater opioid supply is associated with higher interest rates for large bank mortgages, but has no significant relationship for small bank mortgage interest rates. A back-of-the-envelope calculation suggests that the opioid epidemic has cost large bank mortgage borrowers $1.25 billion in additional mortgage payments from 2007 to 2015. I also find evidence that large banks' branch networks induce spillover effects of opioid abuse for interest rates, leading to higher interest rates even for markets with low rates of opioid abuse.

Fifith, I analyze whether the increases in interest rates can be explained by opioid abuse increasing the *ex-post* default risk of mortgages. However, I find little to no significant impact of opioids on default rates for both small and large bank mortgages, suggesting that the risks that opioids impose on mortgage lending arise not directly from borrower default risks, but from search frictions and information costs of finding suitable borrowers in markets suffering from opioid abuse.

Finally, I analyze whether exposure to the opioid epidemic induces changes in banks' balance sheet apart from mortgage credit supplied. In terms of the impact of exposure on portfolio credit risk, I find mixed evidence that higher exposure raises the ratio of charge-offs and non-performing loans to total mortgage lending volume for banks. I also find no evidence that the opioid epidemic has caused banks to shift lending activity away from mortgages and towards other consumer or business loans.

Taken together, my results lend credence to my hypothesis that the channels through which the opioid epidemic affected a lender's mortgage credit supply depends on the size and reach of that lender. Smaller banks, having more geographic constraints and less ability to diversify their borrower pool away from riskier borrowers and communities, were more likely to experience the opioid epidemic as a negative demand shock and were unable to shift lending towards more credit-worthy borrowers or pass on the costs of opioid abuse risk to their borrowers. By contrast, larger banks were able to shift away origination volume and targeted only the most credit-worthy borrowers in exposed areas without reducing their total mortgage lending volume, and were able to pass the costs of opioid abuse risk onto their customers. In general, small banks preserved mortgage credit access and availability[3] in response to local opioid abuse, while large banks preserved the mortgage credit they supplied nationwide in response to the crisis, at the price of higher interest rates for their borrowers.

My findings carry several implications for the literature on the financial impact of the opioid epidemic, and for the role that both small, community-oriented banks and large, national banks play in providing credit supply to consumers on both the local and national scale. First, from a policy making perspective, heterogeneity in responses to a crisis matters when evaluating whether to craft policies that support smaller lenders, which are less likely to reduce credit access or raise lending costs for their local communities that are more in need of financial assistance in recovering from the crisis, or larger lenders that will be more able to absorb the risks associated with the crisis without reducing national credit supply. Second, future researchers should consider the impact of the opioid epidemic not only on the supply of credit, but also on the demand for credit when evaluating the impact of opioid abuse on financial outcomes.

The rest of the paper is organized as follows. In the remainder of this section, I discuss the related literature and the hypotheses to be tested in this paper. Section 2 describes the datasets used in my analysis. My methodology and identification strategy is described in Section 3. Section 4 discusses the impact of exposure to the opioid epidemic on bank lending volume. Section 5 discusses the impact on mortgage interest costs and default risks. Section 6 examines bank balance sheet changes caused by the opioid epidemic. Section 7 concludes.

[3] I define credit access as the total volume of loans provided to mortgage borrowers, while I define credit availability as the ease for individual borrowers to access credit in the form of lower costs.

1.1 Literature Review

The literature on the opioid epidemic was popularized under Case and Deaton, 2015, which noted that "deaths of despair" due to suicides and drug overdoses had contributed significantly to the reversal in rising life expentencies amongst middle-aged white non-Hispanics in the United States. Works such as Finklestein, Gentzkow, and Williams, 2018, Case and Deaton, 2020, and Arteaga and Barone, 2022 further delved into the economic conditions that contributed to the opioid epidemic. They examine how changes in migration patterns and economic opportunities raised the probability for many Americans of dying early due to opioid abuse. They also trace the origin of the epidemic to Purdue Pharmaceuticals, and how their Oxycotin marketing efforts significantly expanded opioid distribution nationwide, creating a nationwide epidemic of opioid abuse.

The opioid literature has since expanded to examine its effects on the real economy. Krueger, 2017, M. C. Harris et al., 2020, Cutler and Glaeser, 2021, and Aliprantis, Fee, and Schweitzer, 2019 study the impact of the opioid epidemic on employment. Langford and Feldman, 2021 and Ouimet, Simintzi, and Ye, 2020 examine its impact on firm outcomes, and find significant reductions in labor supply and increased automation investment due to the epidemic. For financial markets, Cornaggia et al., 2021 finds that opioid abuse reduces the volume and quality of municipal financing, while Custodio, Cvijanovic, and Wiedemann, 2022 finds that higher rates of opioid abuse are significantly linked to lower home values, due to higher rates of mortgage defaults and foreclosures. Karimli, 2022 finds similar results as Custodio, Cvijanovic, and Wiedemann, 2022, linking greater exposure to the epidemic to higher rates of mortgage defaults.

My work is most similar to Jansen, 2022 and Agarwal, Li, et al., 2022, which examine the impact of opioid abuse on consumer credit supply and credit consequences. Both papers link local opioid abuse to consumer credit deterioration in the form of higher loan delinquency and default rates, leading to lenders pricing in the risk of opioid abuse in the form reducing both credit access and availability to consumers. My proposed contribution to the opioid epidemic literature is to focus on how the heterogeneity in lender business models affect the impact of the epidemic on both *lender behavior* and *consumer welfare*. This paper links the literature on the opioid epidemic to the literature on banking competition, particularly on distance (Degryse and Ongena, 2005, Agarwal and Hauswald, 2010) and business models, (Berger et al., 2005, Liberti and Petersen, 2018, Balyuk, Berger, and Hackney, 2022) to better understand the competitive effects of the opioid epidemic on lending markets, particularly in the mortgage sector.

My work is also related to studies in the bank lending channel literature such as Gilje, Loutskina, and Strahan, 2016, Cortés and Strahan, 2017, and Cuñat, Cvijanović, and Yuan, 2018, which examine the impact of exogenous shocks on bank lending activity and portfolio decisions. Gilje, Loutskina, and Strahan, 2016, treating oil and gas discoveries as an local exogenous liquidity windfall, find that bank branch networks help export liquidity to other markets, while Cuñat, Cvijanović, and Yuan, 2018 uses real estate shocks to examine the spillover within banks across geographical locations and business lines. My paper contributes to this literature by combining it with a significant public health issue, as well as examining the heterogeneity in bank responses to economic shocks. If the nature of the shock caused by the opioid epidemic differs between banks, additional questions are raised as to whether such heterogeneity also exists for other types of economic shocks.

1.2 Hypothesis Development

The main focus of this paper is examining how the nature of a financial intermediary impacts how the intermediary experiences a crisis. Specifically, I examine how differences in bank size and geographic diversity affect whether a bank experiences the opioid epidemic as an *increase in credit risk*, or as a *negative demand shock*.

Hypothesis 1: The opioid crisis acts more as a negative demand shock to smaller banks, while larger banks are more likely to treat the epidemic as an increase in credit risk.

The literature examining the opioid epidemic finds significant effects of opioid abuse on both credit supply and demand. On the credit supply side, Agarwal, Li, et al., 2022 and Jansen, 2022 find that lenders restrict credit supply in areas suffering from opioid abuse as a response to a deterioration in consumer credit-worthiness. Similarly, M. C. Harris et al., 2020, Alpert et al., 2021, and Greenwood, Guner, and Kopecky, 2022 link opioid abuse to human capital loss and direct loss to households, as increased usage of opioids may lead to lower labor productivity, consequently leading to lower household income and job loss, even excluding death due to overdose. On the credit demand side, Custodio, Cvijanovic, and Wiedemann, 2022 links opioid abuse to reductions in house prices, suggesting that housing valuation and demand is negatively affected by exposure to the opioid epidemic. Negative labor and productivity shocks brought about by opioid abuse (Ouimet, Simintzi, and Ye, 2020, Aliprantis, Fee, and Schweitzer, 2019) can lead to potential borrowers at the margins to drop out of the mortgage market, due to a deterioration in credit-worthiness, job loss, and even death.

Large banks have greater size, more geographic diversification, and are more reliant on hard information for their lending decisions compared to smaller banks. (Berger et al., 2005, Liberti and Petersen, 2018, Balyuk, Berger, and Hackney, 2022) As such, they are less reliant on communal ties for their mortgage business, and are more likely to treat communities affected by the opioid epidemic as markets with increased credit risk. By contrast, small banks are more reliant on soft information and local communities to foster ties with potential borrowers for future lending business. As opioid abuse in an area increases, losses in income, credit conditions, and even death leads to a reduction the pool of potential borrowers for small banks, constituting a negative demand shock.

For large banks, I expect to see higher denial rates and interest rates for their mortgage lending activity. In addition, banks will be expected to have shifted their lending activity away from more exposed to less exposed areas to reduce their exposure to opioid-induced credit risk. In effect, the opioid epidemic induces large banks to induce local supply shocks to mortgage credit, by making banks more hesitant to originate mortgages in areas more affected by opioids. By contrast, for small banks, I expect to see a reduction in mortgage origination volume that cannot be explained stricter lending standards and higher denial rates for mortgage applications. Furthermore, I expect that the ability of small banks to shift lending towards less exposed markets is reduced, as small banks' smaller size and networks prevent them from shifting lending activity away from areas suffering from opioid abuse.

Hypothesis 2: Small banks are better than large banks at preserving local credit access in response to the epidemic. However, large banks are better at providing national mortgage credit access in response to the epidemic.

If large banks treat the opioid epidemic as a credit risk, then areas that are more exposed to the opioid epidemic become more risky areas to lend to, either due to higher rates of mortality or increased risks of default or foreclosure on mortgage payments. Thus, large banks will want to shift mortgage lending volume away from more exposed to less exposed markets, thereby reducing exposure to opioid risk. Small banks with greater reliance and ties to their local communities will be less likely to reduce lending volume to areas suffering from opioid abuse.

However, large banks' greater number of markets and geographic outreach allow them to shift lending activity away from exposed markets, which small banks are unable to do. Thus, the total national mortgage origination volume of large banks will not be affected by greater exposure to the epidemic, while small banks that are more exposed will suffer greater demand shocks, and thus will suffer greater reductions in total origination volume. Similar results can be found in Cuñat, Cvijanović, and Yuan, 2018, which finds that while both large and small banks reduce lending activity in response to real estate shocks, large banks reduce their total lending relatively less than small banks do, suggesting that banks' internal capital markets play a large role in increasing the resiliency of large bank lending activity.

Hypothesis 3: Large banks, but not small banks, are less likely to approve mortgage applications in areas suffering from opioid abuse.

Since large banks experience the opioid epidemic as a credit risk shock, the reduction in mortgage origination for large banks is driven by large banks restricting the supply of mortgage credit access, by reducing the approval rate of the applications they receive. For small banks, however, their reduction in local lending volume is driven by potential borrowers withdrawing from the market, and not small banks voluntarily restricting mortgage credit access.

Hypothesis 4: Large banks, but not small banks, will raise borrowing costs in response to exposure to opioid abuse.

Large banks are able to pass on the costs associated with opioid abuse risk onto their borrowers, thereby raising interest rates for mortgages originated in highly affected areas to account for the risks of lending to markets with higher opioid abuse rates. Small banks, by contrast, experiencing a reduction in their borrower pool, and more reliant on soft information and personal relationships for lending business, are not able to raise interest rates in response to opioid abuse.

2 Data

Mortgage data: My primary data source for mortgage origination and performance is the HMDA-GSE match that was utilized in Law and Mislang, 2022. This dataset combines the detailed mortgage origination data available via the Home Mortgage Disclosure Act (HMDA) with the loan performance data available from the government-sponsored enterprises (GSEs) Freddie Mac and Fannie Mae. For the period between 2007 and 2015, these data sources are matched using fuzzy data matching techniques that utilize overlapping information between the data sources to identify unambiguously matched loans. This matched data allows me to combine lender information from HMDA with borrower quality (such as LTV, DTI, and

FICO scores) and loan performance information (such as late payments and defaults) from the GSE data sources for the entirety of my sample.[4]

Mortgage data is then supplemented with the Robert Avery lender file to incorporate information about each lender's ultimate parent company.[5] Furthermore, this dataset allows us to match lenders between the HMDA dataset and Call Report data, which is elaborated on below.

Following Duchin and Sosyura, 2014 and Vojtech, Kay, and Driscoll, 2020, I restrict my sample of mortgages to the following conditions: (1) mortgages must either be approved[6] or denied by the mortgage lender, (2) the property must be owner occupied, and (3) the mortgage must be for a 1-4 single family housing unit.

Opioid supply: Data on the supply of opioid prescriptions comes from the DEA's Automation of Reports and Consolidated Orders System (ARCOS) dataset that was provided by the Washington Post in 2020 after a lawsuit for the restricted dataset.[7] The database covers the entire distribution of legal opioid pills sold in the United States from 2006 to 2014, and for each pill sold reports the name, opioid type, dosage, manufacturer, distributor, ultimate retail distributor type,[8] and location at a state and county level.

I also collect data on the aggressiveness of Purdue's marketing efforts on the pre-epidemic era. Following Cornaggia et al., 2021, using archived DEA reports, I gather data on the distribution of oxycodone pills on a ZIP-code basis from 1997 to 2002. Next, I match each 3-digit zip code to a county, based on the county with the highest population in the zip code. Finally, I use the growth rate of oxycodone supply per capita from 1997 to 2002 as my proxy measure of Purdue's Oxycotin marketing efforts before the start of the opioid epidemic.

[4]Public datasets provided by Fannie Mae and Freddie Mac only identify the top ten lenders by volume that securitize their loans with each GSE by year. Using the algorithm in Law and Mislang, 2022, I am able to identify less prolific lenders in the GSE sample, particularly smaller banks, to examine the pricing and performance of their mortgages.

[5]The Robert Avery file is available on Neil Bhutta's website at https://sites.google.com/site/neilbhutta/data.

[6]Includes mortgages that are approved but not accepted.

[7]Source: https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/?nid

[8]Distributor types include chain pharmacies, retail pharmacies, direct prescribers, hospitals, and bulk distributors.

Bank portfolio data: I collect quarterly data on bank's balance sheets, income statements, and branch location from the Consolidated Report of Condition and Income, which are otherwise known as the "Call Reports". Call Reports are collected from the Federal Financial Institutions Examination Council (FFIEC) Central Data Repository's Public Data Distribution website. Every national bank, state member bank, and insured nonmember bank is required by the FFIEC to file a Call Report each calendar quarter. I restrict my sample of lenders to depository institutions[9] with Call Report data in the previous year, and classify lenders as small banks if their total assets fall below $10 billion, and large lenders otherwise.

County economic and demographic data: I collect data from the US Census and Bureau of Labor Statistics on county level economic and demographic statistics. I also use FHFA housing price index data to control for house price growth in mortgage lending decisions.

Medicare Data: From the CMS website, I collect county-year level data on the population that is eligible for Medicare Part-D. Since the data is available on a monthly basis, I use December as my yearly measure of eligibility. I combine the data with the Census data to calculate the percentage of the population that is eligible for Medicare Part-D. I also use a similar process to collect data on the proportion of the population that has enrolled in Medicare Part-D. The data on Medicare Part-D enrollment spans from 2008 to 2015.[10]

Table 1 shows the summary statistics of our sample. Panel A summarizes the county-level demographic and economic variables, along with the opioid supply and instrumental variables. ($PurdueMkt$ and $EligibilityRate$) Opioid supply is measured in morphine gram equivalents (MGE) per capita, which equals the average amount of opioid pills per capita distributed in each county-year observation, scaled by the potency of each pill.[11] Figure 1

[9]Excluding credit unions.

[10]Due to privacy concerns, any population count is censored if the count falls at or below 10, which may bring about concerns regarding left-censoring. However, when analyzing the data for Medicare enrollment, this issue does not occur very frequently.

[11]In practice, opioid pill potency is measured in morphine milligram equivalents (MME), but I scale the measure to an MGE equivalent for ease of interpretation.

shows the average annual MGE per capita of each county in our sample from 2006 to 2015. I use the county level supply of opioids per capita as my measure of opioid abuse in this paper.

Panel B summarizes the bank balance sheet data from Call Reports, along with their overall exposure to the opioid epidemic, $BankExposure$. $BankExposure_{b,t}$ is equal to the weighted average of opioid supply in counties c where lender b has a branch, weighted by the percentage of total deposits $w_{b,c,t}$ the lender l has in that branch.

$$BankExposure_{b,t} = \sum_{i} w_{b,c,t} OpioidSupply_{c,t}$$

I use $BankExposure$ as a measure for a bank's overall exposure to the opioid epidemic, and in later regressions will examine how exposure to the epidemic affects both a bank's total lending, as well as whether a bank's exposure to the epidemic creates spillover effects into markets that would otherwise be unaffected by the opioid epidemic.

3 Methodology

The main endogeneity concern for this study is that opioid supply and mortgage lending may be jointly driven by local economic conditions. In order to alleviate endogeneity concerns, the main specification for this study is a two-stage least squares regression with two instruments that are highly correlated with county-level opioid supply, but should not affect mortgage lending outcomes through alternative channels.

My first stage model regresses a county's opioid supply on both the county's Purdue's Oxycotin marketing efforts pre-epidemic, and its Medicare Part-D eligibility rate.

$$\begin{aligned} OpioidSupply_{c,t-1} = \gamma_0 + \gamma_1 PurdueMkt_c + \gamma_2 Eligibility_{c,t-1} + \gamma_3 CountyControls_{c,t-1} \\ + \gamma_4 BankControls_{b,c,t-1} + \delta_c + \nu_t + \pi_{b,c} + \mu_{c,t} \end{aligned} \tag{1}$$

$OpioidSupply_{c,t-1}$ equals the per capita opioid supply in county c in year $t-1$, scaled by MGE. Following Ouimet, Simintzi, and Ye, 2020 and Aliprantis, Fee, and Schweitzer, 2019 $CountyControls_{c,t-1}$ include the male population ratio, population ratios for white, black, Hispanic, and Native-American populations, population ratios for ages 20-64 and ages 65 and over, the migration inflow ratio, poverty ratio, unemployment ratio, labor force participation ratio, and neoplasm mortality. I also include house price and house price growth over time, deflated by the national GDP price index.[12] $BankControls_{b,c,t-1}$ borrows from Gilje, Loutskina, and Strahan, 2016, and includes log assets, and the ratios of each of deposits, liquid assets, C&I loans, total mortgage volume, tier 1 and tier 2 capital, loan commitments, and letters of credits, scaled to total assets. Fixed effects include state fixed effects δ_c, year fixed effects ν_t, and lender by state fixed effects $\pi_{b,c}$.[13]

My identification strategy relies on the exclusion restriction assumption that my instrumental variables impact the rate of opioid abuse in a county, but do not directly impact bank credit supply. I use two different instrumental variables as different proxies for opioid supply. The first instrumental variable, following Cornaggia et al., 2021, is $PurdueMkt_c$, which equals the growth rate of oxycodone pills distributed between 1997 and 2002 for a county c. This instrument is a proxy for the aggressiveness of Purdue marketing of Oxycotin in an area before the outbreak of the opioid epidemic.

The second instrumental variable, $Eligibility_{c,t-1}$, equals the eligibility rate of the population in county c in year $t-1$ for Medicare Part-D. Beneficiaries of Medicare Part-D significantly reduces the costs of prescription drugs, including opioids. Eligibility for Medicare Part-D comes via being eligibile for Medicare, and then either via age qualification at 65 years of age, or having certain qualifying disabilities, end stage renal disease (ESRD), or amyotrophic lateral sclerosis (ALS).[14] I use county-level measures of Part-D eligibility as

[12] Data taken from the BEA: https://www.bea.gov/data/prices-inflation/gdp-price-index

[13] For most regressions, I do not use county fixed effects, since $PurdueMkt$ is a county-level time-invariant measure, thus creating perfect correlation between county fixed effects and $PurdueMkt$ and thus making my matrix non-invertible.

[14] There may be concerns about using Medicare Part-D Eligiblity as an instrument, while also having the share of a county's population above 65 years old as a separate control variable. Powell, Pacula, and Taylor, 2020, the first paper to the best of my knowledge to discover the impact of Medicare Part-D on opioid supply, also included age categories as control variables in their model, while also having Part-D eligibility as their main independent variable of interest. Furthermore, the additional pathways to Part-D eligibility makes it likely that my instrument captures significant effects that are not captured by age alone.

an explanatory variable for a county's opioid supply that is, surprisingly, directly linked to opioid abuse amongst the working age population due to diversion of opioid supply from Part-D beneficiaries.

In the public health literature, papers such as Powell, Pacula, and Taylor, 2020 and M. C. Harris et al., 2020 found that the expansion of Medicare Part-D eligibility in a community lead to significantly higher death rates and reduction in labor productivity. Surprisingly, the impact of opioid abuse was strongest amongst the population ineligible for Medicare Part-D, suggesting that diversion of opioid prescriptions was the main driver of opioid abuse post-Medicare expansion. The expansion of opioid supply due to Medicare expansion led to significant spillover rates in drug-related mortalities occured in populations under 65 years old, which (1) correlates almost perfectly with the population ineligible for Medicaid Part-D, and (2) is associated with the increase in deaths amongst the working age population attributed to the opioid epidemic in the literature.

To test the assumption that opioid supply depends on both Purdue's Oxycotin marketing efforts pre-epidemic, and on Medicare Part-D expansion, Table 2 shows the results of the first stage model regressing opioid supply on our proposed instruments. I include Columns (1) and (3) show the results regressing only on $PurdueMkt$ and *Eligibility*, while Column (2) includes the result for an alternative instrument *Enrollment*, which equals the percentage of a county population that has already enrolled for Medicare Part-D. Comparing the results for $PurdueMkt$ and *Eligibility* versus those for *Enrollment*, the adjusted R^2 values for Column (2) is 0.384, significantly smaller than those for Column (1) and (3) (0.491 and 0.453 respectively). Furthermore, when I combine *Enrollment* with either $PurdueMkt$ and/or *Enrollment* in Columns (4) and (6), the coefficient for *Enrollment* becomes insignificant. By contrast, the coefficients for both $PurdueMkt$ and *Eligibility* remain significant even when combined in a single model, as shown in columns (5) and (6).

Additionally, from a graphical perspective, Figure 2 displays the values for $PurdueMkt$ and *Eligibility* for each county geographically, while Figure A1 displays the same for enrollment rates. When I compare with Figure 1, I see significant overlap between counties with the highest measures of $PurdueMkt$ and $Eligibility$ and the highest amounts of per capita opioid supply (West Coast, coast of Florida, and Appalichian region), while the counties with the highest $Enrollment$ values have little overlap with $OpioidSupply$. Thus, I choose to only use $PurdueMkt$ and $Eligibility$ as our instrumental variables for the remainder of my analysis.[15]

My second stage model, where $Y_{b,c,t}$ is the outcome variable of interest, is:

$$\begin{aligned} Y_{b,c,t} = \beta_0 + \beta_1 \widehat{OpioidSupply}_{c,t-1} + \beta_2 CountyControls_{c,t-1} \\ + \beta_3 BankControls_{b,t-1} + \delta_s + \nu_t + \pi_{b,s} + \epsilon_{b,c,t} \end{aligned} \tag{2}$$

The main coefficient of interest, β_1, measures how lenders respond to increases in opioid abuse rate in a local mortgage market at the county level. I measure that impact in terms of (a) mortgage volume, (b) approval rates, (c) interest rates, and (d) default rates, to measure the difference in impact the opioid epidemic has on small and large banks, and whether different lenders experience the epidemic as either a demand shock or a supply (credit) shock.

4 Lending Volume and Opioid Abuse

I first test Hypothesis 1 and 2 by examining the impact of opioid supply on mortgage credit access provided by banks. I construct a panel dataset of bank-county-year observations that aggregates mortgage origination volume for banks in individual counties. Following Gilje, Loutskina, and Strahan, 2016 and Cortés and Strahan, 2017, a bank-county-year observation is recorded if the bank originated any mortgages in the county in the preceding year.

I find that on a local level, higher rates of opioid abuse lead to both small and large banks reducing origination volume and exiting a market. Compared to small banks, however, large

[15] There are additional reasons why I choose to use Medicare Part-D eligibility rates over enrollment rates. First, Powell, Pacula, and Taylor, 2020 links increases in opioid abuse to increases in opioid supply from Part-D expansion, rather than enrollment in Part-D directly. Secondly, data for Part-D enrollment suffers heavily from left-censoring for county-level observations below 10, which may lead to significant bias in our sample.

banks reduce origination volume to a greater extent, and are more likely to exit a market. On the other hand, on a aggregate nationwide level, exposure to the opioid crisis causes small banks to significantly reduce total mortgage origination, while having no effect for large banks.

Following the banking literature, I also test Hypothesis 3 and examine changes in approval rates on both the aggregate county level, and on the individual loan level, to determine whether reductions in in lending volume are driven by supply or demand-side factors. On a county level, I find significant negative effects for local opioid supply on large bank approval rates, but not for small banks. Taken together, these results provide significant evidence for Hypotheses 1 and 2, in that the reduction in origination volume for small banks is driven by negative demand shocks, but for large banks is driven by lenders shifting mortgage credit access away from areas more affected by the opioid epidemic.

4.1 Origination Volume

4.1.1 Local Exposure

Table 3 shows the 2SLS results for Eq. 2, regressing county-level log mortgage lending volume for banks on $OpioidSupply$, instrumented by $PurdueMkt$ and $Eligibility$.[16] Columns (1) to (3) showcase the results for small banks, while Columns (4) to (6) showcase the results for large banks. Columns (1) and (4) shows the results for mortgages for both home purchases and refinancing mortgages, Columns (2) and (5) shows the results for only purchase mortgages, and Columns (3) and (6) shows the results for only refinancing mortgages. I also report the F-statistics for each Column to test for weak instruments. Following the $F > 10$ rule-of-thumb cutoff for weak instruments, (Staiger and Stock, 1997) only Column (3) reports weak instruments for $OpioidSupply$, which is also the only column with an insignificant β_1.

Comparing the coefficients for $OpioidSupply$ for small banks compared to large banks, I find that *large banks reduce lending volume more than twice as much as small banks in*

[16] OLS estimates are displayed in Table A2.

response to higher rates of opioid abuse. As shown by the coefficient β_1, an increase in 0.1 in *OpioidSupply* leads to small banks reducing lending volume by an additional 20%, and large banks by an additional 40%. Furthermore, for refinancing mortgages as shown in Columns (3) and (6), β_1 is insignificant for small banks, but significant and negative for large banks.

Table 4 shows similar results when I regress the probability of a bank exiting a county's mortgage market on the supply of opioids. Instead of log mortgage volume, I use an indicator variable for whether a bank has originated any loans in a market. Comparing Column (1) with Column (4), β_1 is 55.5% larger for large banks compared to small banks, suggesting that large banks are more likely to withdraw from a market in response to opioid abuse than small banks are. A one standard deviation increase in *OpioidSupply* raises the probability of exit by 2.7% for small banks, and by 4.2% for large banks. When I examine β_1 for purchase and refinancing mortgages separately, β_1 is consistently larger for large banks (and for refinancing loans, more statistically significant) than for small banks, suggesting that this pattern persists regardless of the type of mortgage that is originated. Taken together, Tables 3 and 4 suggest that large banks are more likely to reduce mortgage origination activity in areas that have been harder hit by the opioid epidemic.

4.1.2 National Exposure

Next, I look how a bank's nationwide, rather than local, exposure to the opioid epidemic affects the total amount of credit access they provide. I run the following model regression a bank's log total mortgage lending volume across the U.S. on the bank's exposure to the opioid epidemic, removing geographic controls and fixed effects from Eq. 2.

$$\begin{aligned} Log(TotalMortgageVolume)_{b,t} = \lambda_0 &+ \lambda_1 BankExposure_{b,t-1} \\ &+ \lambda_2 BankControls_{b,t-1} + \nu_t + \pi_b + \epsilon_{b,t} \end{aligned} \tag{3}$$

Table 5 displays the results of Eq. 3. My main coefficient of interest is λ_1, which measures the impact of a bank's exposure to the opioid epidemic on its total mortgage origination volume. For small banks, λ_1 is consistently negative and significant for Columns (1) to (3).

However, for large banks, λ_1 is never statistically significant. As such, Table 5 suggests that greater exposure to the opioid epidemic leads to small banks reducing their overall mortgage business, but not for large banks.

Combining the findings in Tables 3 and 4 with the findings from Table 5, I find significant evidence that Hypothesis 2 is correct. The findings suggest that small banks, due their smaller size and geographic diversification, are less able to shift mortgage lending activity away from areas with higher rates of opioid abuse, leading to them internalizing the opioid epidemic as a negative demand shock. By contrast, large banks are able to shift origination activity away from areas suffering heavily from the opioid epidemic, thereby shielding their mortgage business activities from exposure to risks associated with lending to areas with higher rates of opioid abuse.

4.2 Approval Rates

To test Hypothesis 3, and determine whether the changes in origination volume by small and large banks are demand driven or supply driven, I next examine the impact of opioid supply on mortgage application approval rates. On both on a county level for Table 6 and on an loan level for Table 7, I examine decreases in lending volume are driven through a supply channel (lenders being less willing to approve applications), or through a demand channel (fewer borrowers applying for a mortgage).

Table 6 displays the results for Eq. 2, with $Y_{b,c,t}$ being equal to the approval rate of mortgages in a county c for lender b in year t, divided between all, purchase, and refinancing mortgages. For small banks, Columns (1) to (3) display no correlation between mortgage approval rates and opioid supply, suggesting that reductions mortgage origination volume are mainly driven by demand-side factors. By contrast, Columns (4) to (6) display significant negative correlation between opioid supply and approval rates for large banks, suggesting a supply channel effect in reductions in origination volume.

To examine the effect of opioid supply on an individual loan level, I run the following model regressing individual mortgage application approval on opioid supply:

$$I(Approved)_{l,b,c,t} = \mu_0 + \mu_1 OpioidSupply_{c,t-1} + \mu_2 BankControls_{b,t-1} + \mu_3 CountyControls_{c,t-1} + \mu_4 BorrowerControls_{l,t} + \delta_c + \nu_t + \pi_{b,c} + \epsilon_{l,b,c,t} \tag{4}$$

$I(Approved)_{l,b,c,t}$ is an indicator variable for whether a mortgage application l to lender b in county c in year t has been approved. $CountyControls$ and $BankControls$ are the same as in the previous regressions, while $BorrowerControls$ include the log mortgage principal, log borrower income, minority status, sex, and lien status. In addition, for some regressions I also include the variable $I(LTV > 3)$ as a proxy for the riskiness of the borrower, along with an interaction term between $OpioidSupply$ and $I(LTV > 3)$ to examine whether lenders choose to deny applications to riskier lenders in the presence of greater opioid abuse. An issue with HMDA is that due to privacy concerns, I am unable to directly observe more traditional proxies for borrower risk such as credit scores, loan to value, and debt to income ratios from application data directly. Instead, I use $I(LTV > 3)$, which is an indicator variables for whether the loan-to-income ratio for an application is greater than 3, as a proxy for borrower risk as a substitute.

Table 7 displays the results of Eq. 4. Panel A displays the results for purchase mortgages, and Panel B displays the results for refinancing mortgages. For small banks, Column (1) shows some evidence of small banks reducing the likelihood of approval in markets with greater opioid supply, but Column (2) suggests the effect to be limited to reducing approvals for the applications of relatively more risky borrowers, as the coefficient for $OpioidSupply$ is statistically insignificant, while the coefficient for $OpioidSupply \times I(LTV > 3)$ is both significant and negative. For large banks, Panel A shows no evidence of opioid supply affecting approval rates for purchase mortgages, while Panel B shows both a significant and negative effect of opioid supply on approval rates for refinancing loans.

5 Mortgage Costs and Opioid Abuse

5.1 Interest Rates

5.1.1 Local Exposure

Having established my results for lending volume, I next test Hypothesis 4 and examine how different lenders adjust the costs of mortgage passed on to lenders in response to the opioid epidemic. Table 8 displays the results for Eq. 2 using mortgage interest rates as the outcome variable. In addition to county and lender controls, I also add in borrower controls such as the ones previously used for mortgage approval rates, and variables collected from GSE datasets, specifically credit scores, LTV and DTI ratios, and number of borrowers.[17] I replace year and state fixed effects with month and county fixed effects to better control for unobserved heterogeneity across time and geographies, respectively.[18] Table 8 displays the results of the 2SLS regression.[19] The dependent variable of interest is the $InterestRate$, expressed in percentage points, of a mortgage, and the main independent variable of interest is $OpioidSupply$, which measures the impact of a lender's local exposure to opioid abuse on the interest rates charged by the lender.

For small banks, Columns (1) and (3) show no change in mortgage interest rates in relation to local opioid supply. For large banks however, Columns (2) and (4) suggest that lenders significant raise interest rates in response to opioid supply. A one SD increase in $OpioidSupply$ raises large bank interest rates by 25-29 basis points. To quantify the economic impact of these changes, a back-of-the-envelope calculation suggests that during the timeframe of our sample between 2007 and 2015, consumers paid a total of $1.25 billion

[17]Credit scores and LTV ratios are binned in a similar fashion to a Fannie Mae/Freddie Mac eligilibity matrix in order to more closely mimic how GSEs price the risks of underwriting loans. DTI is binned in a similar fashion to how debt-to-income scores are binned in the public HMDA dataset post-2018, and number of borrowers are binned with regards to whether there is more than one borrower for a mortgage, or not.

[18]County fixed effects are possible in this regression, as with multiple observations for the same county, singular matrices are no longer a concern.

[19]OLS results are shown in the Appendix in Table A4

in additional interest payments due to the opioid epidemic.[20][21]

In summary, I find significant evidence that Hypothesis 4 is correct, in that large banks but not small banks increase interest rate costs in response to exposure to opioid abuse. This lends further credence to Hypothesis 1 in that small banks experience the opioid epidemic as a negative demand shock, but large banks experience exposure to the epidemic as a credit risk. Large banks reduce the supply of credit to mortgage borrowers at both the extensive margins (lower origination volume) and intensive margins (higher interest rates) in response to higher rates of opioid abuse, shifting credit supply away from highly exposed areas to reduce exposure to the lending risks associated with opioid abuse. Small banks, by contrast, lacking the size and branching networks of large banks, are unable to pass on these costs to their borrower pool, and thus are unable to make up the loss in origination volume with higher profit margins.

5.1.2 Spillover Effects

I also analyze whether local or national exposure to the opioid epidemic has a greater effect on interest rates. To proxy for a lender's nationwide exposure to the epidemic, I add the *BankExposure* variable from Eq. 3 as a measure of a bank's total exposure to the opioid epidemic, and compare the effects to the bank's local exposure as measured by *OpioidSupply*. The results are shown in Table 9. For small banks (Columns (1) and (3)), the coefficient for *OpioidSupply* and *BankExposure* are both insignificant. For large banks (Columns (2) and (4)), the effects of *OpioidSupply* become absorbed by *BankExposure*, which have nearly the same coefficients as *OpioidSupply* in the previous model for Table 8.

The findings from Table 9 provide evidence of the opioid epidemic creating spillover

[20] Annual interest rate payments were calculated by summing the total amount of loans originated in our sample by large banks each year by loan purpose, and then multiplying by the respective coefficient in Table 8 scaled to basis points, times the average value of *OpioidSupply*, to get the average value of annual interest payments between the year of origination and 2015.

[21] Since the data for interest rates is taken from securitized loans, banks do not profit from higher interest rates in my matched sample, and thus have less incentives to raise interest rates. Thus, the coefficients should be considered as a lower bound on the effect of opioid abuse for interest rates.

effects for large bank mortgage interest costs, as credit risk is transmitted throughout the banking network, rather than remaining confined to the local area. This is consistent with Agarwal, Li, et al., 2022, which suggests that banks with higher exposure to the opioid epidemic transmit increased credit risk across the entire consumer portfolio. This finding is also consistent with the banking literature that states that banks do not borrow and lend locally, but rely on their internal capital markets to make lending decisions. (Cuñat, Cvijanović, and Yuan, 2018) Table 9 suggests that for large banks, credit risk created by opioid abuse is transmitted across bank networks, thereby raising the costs of borrowing for all borrowers in the network, regardless of local opioid abuse rates.

5.2 Borrower Risk

My previous regression models for interest rates controlled for income, credit scores, LTV ratios, and DTI ratios to determine whether increases in interest rates in areas with greater opioid abuse could be explained by *ex-ante* measures of borrower risk. Even controlling for these factors, I still found significant increases in large bank interest rates in highers with greater opioid supply. However, it is possible that the increases in interest rates are explainable by *ex post* borrower default risk. To analyze this possibility, I regress the probability that a loan originated by a lender goes into default on local opioid abuse rates. Table 10 displays the results of the 2SLS model for Eq. 2, where the outcome variable of interest is an indicator variable for a mortgage becoming delinquent for over 90 days.

Surprisingly, and in contrast with Agarwal, Li, et al., 2022 and Jansen, 2022, I find no correlation between opioid abuse and mortgage default rates for either small or large banks. In fact, Column (4) shows statistically significant (although weak ($F < 10$)) evidence of opioid supply being correlated with lower default rates for large bank refinancing mortgages. This result suggest that for large banks, the risks of lending to areas with greater opioid abuse are less associated with higher default rates and borrower credit-worthiness, and more related to search frictions and information costs in finding suitable borrowers. For small banks, if opioid abuse creates a negative demand shock at the margins, thereby removing the least credit-worthy borrowers from the demand pool, it is possible to see why a rise in opioid usage would cause no corresponding increase in default rates, as the borrowers most likely to default would also be the ones most likely to withdraw from the market due to overdosing on opioids.

6 Balance Sheet Changes

Having established significant impacts of the opioid impact on the mortgage lending activities for banks, I now examine whether and how banks are affected by the epidemic on their overall balance sheet. I examine whether banks' mortgage portfolio credit risks have increased, by analyzing whether the ratio of charge-offs and non-performing loans for mortgages have increased, and whether banks have shifted towards alternative lending activities to compensate for the loss in mortgage lending business. Overall, I find mixed evidence that the mortgage portfolio credit risk of banks has significantly increased with exposure to the opioid epidemic, and no evidence that banks have shifted to alternative lending models away from mortgages in response to the opioid epidemic.

6.1 Charge-offs and Non-performing Loans

While the previous section has found no significant impact of opioids on individual borrower default risk, it is possible that significant effects of opioids on credit risk may be found by analyzing total mortgage charge-offs and non-performing loans recorded on a bank's balance sheet. Table 11 displays the results for Eq. 3, replacing the dependent variables of interest with mortgage charge-offs and non-performing loans as a percentage of total mortgage volume. For small banks, I find that exposure to the opioid epidemic is significant and negative for charge-offs, but is positive for non-performing loans. For large banks, I find that exposure has a significant and positive effect for charge-offs, but no effect for non-performing loans. Overall, for both small and large banks, I find mixed evidence on whether opioids increase the overall mortgage portfolio credit risk of banks.

6.2 Shifts in Lending Composition

Beyond mortgages, banks are also engaged in a wide array of consumer and industrial loans, which gives them the option to shift lending activity away from mortgages and towards alternative business activities. To determine whether banks compensate for the reductions in mortgage volume by shifting lending activity away from mortgages, I regress different lending activities on nationwide exposure to the opioid epidemic. Table 12 displays the results of this regression, which uses a similar model with the same controls and fixed effects as Eq. 3. The main output variables of interest are alternate lending activities such as commercial mortgages, credit card loans, consumer loans, commercial and industrial loans, construction loans, and agricultural loans, each scaled by the percentage of a bank's total assets. If banks are significantly shifting away from mortgages to other forms of lending due to opioid exposure, λ_1 should be significant and positive in at least one regression. However, Table 12 finds no significant and positive value of λ_1 in any of the columns, thus providing no evidence that banks are shifting away from mortgage lending to other types of lending in response to the opioid epidemic.

7 Conclusion

I study the impact of the opioid epidemic on bank lenders in the mortgage market, with a particular focus on the heterogeneity in the impact that opioid abuse has on the mortgage lending business of both small and large banks. I find significant evidence that smaller banks are more likely to internalize the opioid epidemic as a negative demand shock, whereas large banks are more likely to treat the opioid epidemic as a credit shock. Local exposure to the opioid crisis causes both small and large banks to reduce mortgage origination volume, but the reduction in volume for large banks is driven more by a drop in approval rates, while the reduction for small banks is driven more by a reduction in consumer demand. However, large banks' advantages in size and geographic diversification allows them to shift mortgage activities away from areas that are more exposed to the opioid epidemic, thereby reducing exposure to opioid abuse risk and allowing them to preserve total origination volume. Furthermore, large banks also charge significantly higher interest rates with greater exposure to the opioid epidemic, which cannot be explained as compensation for higher default risk, for which I find no evidence. Thus, evidence points to large banks shifting the costs associated with the risks of opioid abuse onto their borrowers, while small banks do not. As such, large banks' internalization of the opioid epidemic as a credit risk leads to reductions in credit access and credit availability in the most heavily opioid-supplied markets, while small banks' experience of the epidemic as a negative demand shock blunts these effects for their consumer base.

My findings carry several implications from both an academic and policy making standpoint. From an academic standpoint, to the best of my knowledge, the majority of financial research is inclined to treat the opioid epidemic from a lender perspective as a straightforward increase in borrower credit risk. Acknowledging that opioid abuse can also constitute a negative demand shock can allow researchers to gain better insight into the nuances of how differences in the size and scope of financial intermediaries affect their lending behavior, and thus onto consumer outcomes. From a policy maker standpoint, small banks seem better able than large banks at preserving credit access and availability in response to a crisis, while large banks are better able to preserve total credit access by shifting lending away from exposed areas. Supporting smaller, more community oriented banks will help areas that are more heavily exposed to a crisis, while supporting larger banks helps preserve mortgage credit access to a wider audience.

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Table 1: Summary Statistics

Panel A: Demographic and Economic Variables

	N	Mean	SD	Median	Min	Max
Total Population	31425	98652	315440	25701	61	10085416
Male Population (%)	31425	49.99	2.23	49.55	42.63	72.12
Age 20-64 (%)	31425	57.75	3.41	57.78	7.78	82.84
Age 65+ (%)	31421	16.30	4.34	15.94	2.88	54.32
White Population (%)	31425	85.65	16.39	92.63	2.61	99.69
Black Population (%)	31425	9.09	14.55	2.17	0.00	86.15
Native Population (%)	31425	1.13	5.60	0.19	0.00	96.48
Hispanic Population (%)	31425	8.40	13.22	3.38	0.00	96.33
Labor Force Participation (%)	31373	48.24	6.92	48.45	14.28	132.42
Unemployment Rate	31373	6.98	3.00	6.50	1.10	29.40
Poverty Ratio (%)	31395	16.35	6.42	15.40	0.00	62.00
Median Income	31395	44409.93	11574.45	42380.00	0.00	125900.00
HPI	27476	265.52	167.72	210.85	63.69	1785.72
Neoplasms per capita	29237	261.089	256.137	75.387	36.841	929.900
OpioidSupply	26823	0.322	0.248	0.272	0.00	3.16
PurdueMkt	7190	368.984	241.805	341.980	−41.007	2072.057
Eligibility	25087	19.411	4.821	19.406	2.224	53.167

Panel B: Bank Variables

	N	Mean	SD	Median	Min	Max
Log Assets	71,222	12.061	1.382	11.932	4.190	21.453
Liquid Assets/Assets	71,222	0.270	0.167	0.240	0	1
Deposits/Assets	71,222	0.816	0.129	0.846	0	1.056
Liabilities/Assets	70,630	0.877	0.102	0.897	0	1.234
Net Income/Assets	71,222	0.007	0.162	0.008	34.710	21.720
Interest Expense/Assets	71,222	0.003	0.003	0.002	0	0.290
Loan Commitments/Assets	71,222	0.006	0.113	0	0	8.830
Letters of Credit/Assets	71,222	0.0004	0.006	0	0	0.288
Tier 1 Capital/Assets	71,222	0.116	0.096	0.097	0	1.029
Tier 2 Capital/Assets	71,222	0.008	0.004	0.008	0	0.099
Provision of Loan and Lease Losses/Assets	71,222	0.004	0.011	0.001	1.621	0.526
Bank Exposure	70,100	0.639	0.422	0.548	0	5.259

This table reports the summary statistics for all counties and banks in my sample between 2006 and 2015. Variables used as controls in later regressions are unbolded and unitalicized, key independent variables are bolded, and instrumental variables are in italics. Panel A reports county-year observations of economic, demographic, and opioid-related variables. Data on economic and demographic variables are taken from the ACS 5-year survey, Bureau of Labor Statistics. Data on opioid supply and Purdue marketing efforts are taken from ARCOS. Data on Medicare Part-D eligibility and neoplasm deaths per capita are taken from the CDC. Panel B reports bank-year level variables calculated from end-of-year Call Report data.

Table 2: Drivers of County-level Opioid Supply

	OpioidSupply					
	(1)	(2)	(3)	(4)	(5)	(6)
$PurdueMkt$	0.012***			0.014***	0.011***	0.013***
	(0.004)			(0.004)	(0.004)	(0.004)
$Enrollment$		0.012***		0.003		−0.008
		(0.003)		(0.005)		(0.005)
$Eligibility$			0.036***		0.050***	0.052***
			(0.004)		(0.008)	(0.011)
County Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Observations	6,422	6,693	18,884	1,448	4,997	1,448
Adjusted R^2	0.491	0.384	0.453	0.477	0.506	0.509
Note:				*p<0.1; **p<0.05; ***p<0.01		

This table reports the first-stage regressions of the key instrumental variables ($PurdueMkt$ and *Eligiblity*), as well as an alternate unused instrumental variable (*Eligibility*), on county-level opioid supply. $PurdueMkt$ equals the county growth rate of per-capita opioid supply between 1997 and 2002. *Eligiblity* equals the percentage of the county population eligibile for Medicare Part-D. *Enrollment* equals the percentage of the county population enrolled in Medicare Part-D. County controls include all county control variables reported in Table 1 Panel A. All regressions include year and state fixed effects. Standard errors are clustered by county, and are reported in parentheses below coefficient estimates.

Table 3: Local Opioid Supply and Bank Lending Volume

	Log(Mortgage Volume)					
	Small Bank			Large Bank		
	All	Purchase	Refinancing	All	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
OpioidSupply	-1.976^{***}	-2.761^{***}	-0.825	-4.026^{***}	-5.730^{***}	-4.517^{***}
	(0.533)	(0.589)	(0.628)	(0.769)	(0.816)	(0.859)
County Controls	X	X	X	X	X	X
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Lender × State FE	X	X	X	X	X	X
Observations	354,785	354,785	354,785	74,189	74,189	74,189
Adjusted R^2	0.171	0.229	0.242	0.470	0.494	0.482
F-stat	13.74	21.94	1.728	27.41	49.36	27.66

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports 2SLS estimates for the impact of local opioid abuse on mortgage lending volume for small and large banks. *Log*(Mortgage Volume) equals the log annual dollar volume of owner occupied single family mortgages originated by a lender in a county. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). *OpioidSupply* is instrumented by *PurdueMkt* and *Eligiblity*. County controls include all county control variables reported in Table 1 Panel A. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, state, and lender by state fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 4: Opioid Supply and Probability of Bank Exit

	I(Bank-County Volume > 0)					
	Small Bank			Large Bank		
	All	Purchase	Refinancing	All	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
OpioidSupply	-0.110^{***}	-0.192^{***}	-0.034	-0.171^{***}	-0.346^{***}	-0.243^{***}
	(0.034)	(0.041)	(0.044)	(0.047)	(0.058)	(0.058)
County Controls	X	X	X	X	X	X
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Lender × State FE	X	X	X	X	X	X
Observations	354,785	354,785	354,785	74,189	74,189	74,189
Adjusted R^2	0.111	0.193	0.208	0.357	0.418	0.383
F-stat	10.66	21.97	0.619	13.14	36.21	17.29

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the impact of local opioid abuse on the probability that small and large banks exit a local lending market. I(Bank-County Volume > 0) is an indicator variable for whether a lender has originated more than zero owner occupied single family mortgages in a county in a year. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). *OpioidSupply* is instrumented by $PurdueMkt$ and *Eligiblity*. County controls include all county control variables reported in Table 1 Panel A. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, state, and lender by state fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 5: Opioid Exposure and National Mortgage Lending

	Log(Total Mortgage Volume)					
	Small Bank			Large Bank		
	All	Purchase	Refinancing	All	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
BankExposure	-0.345^{***}	-0.333^{***}	-0.797^{***}	-3.416	1.884	-1.981
	(0.105)	(0.122)	(0.153)	(2.768)	(1.628)	(2.722)
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X
Observations	31,765	31,765	31,765	381	381	381
Adj. R^2	0.533	0.544	0.544	0.562	0.698	0.547

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the impact of national exposure to the opioid epidemic on national mortgage lending volume for banks. *Log*(Total Mortgage Lending) log dollar volume of all owner occupied single family mortgages originated by a lender in a year. *BankExposure* equals the average county per capita opioid supply in counties where the lender has a branch in, weighted by deposit share. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year and lender fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 6: Opioid Supply and County Approval Rates

	Approval Rate					
	Small Bank			Large Bank		
	All	Purchase	Refinancing	All	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
OpioidSupply	-0.006	-0.020	-0.010	-0.084^{***}	-0.084^{**}	-0.061^{***}
	(0.013)	(0.017)	(0.016)	(0.026)	(0.036)	(0.023)
County Controls	X	X	X	X	X	X
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
State FE	X	X	X	X	X	X
Lender x State FE	X	X	X	X	X	X
Observations	433,687	275,956	321,220	131,795	81,844	115,957
Adjusted R^2	0.154	0.127	0.164	0.269	0.188	0.238
F-stat	0.243	1.303	0.400	10.93	5.335	7.267

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the impact of local opioid abuse on the approval rate of mortgage applications submitted to banks. *ApprovalRate* is equal to the fraction of owner occupied single family mortgage applications approved by a lender in a county-year. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). *OpioidSupply* is instrumented by *PurdueMkt* and *Eligiblity*. County controls include all county control variables reported in Table 1 Panel A. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, state, and lender by state fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 7: Opioid Supply and Approval Rates for Individual Applications

	Approval			
	Small Bank		Large Bank	
	(1)	(2)	(3)	(4)
Panel A: Purchase Mortgages				
OpioidSupply	-0.012^{*}	-0.011	-0.01	-0.004
	(0.008)	(0.008)	(0.008)	(0.009)
$I(LTI > 3)$		-0.003		-0.027^{***}
		(0.002)		(0.002)
OpioidSupply $\times$ $I(LTI > 3)$		-0.026^{***}		-0.01
		(0.005)		(0.005)
Adj. R^2	0.131	0.131	0.077	0.078
Observations	4,675,680	4,675,680	9,715,847	9,715,847
Panel B: Refinancing Mortgages				
OpioidSupply	-0.017^{*}	-0.013	-0.032^{**}	-0.029^{**}
	(0.009)	(0.009)	(0.014)	(0.014)
$I(LTI > 3)$		-0.048^{***}		-0.069^{***}
		(0.003)		(0.005)
OpioidSupply $\times$ $I(LTI > 3)$		-0.023^{***}		-0.012
		(0.007)		(0.013)
Adj. R^2	0.136	0.138	0.116	0.118
Observations	5,403,503	5,403,503	19,767,101	19,767,101
County Controls	X	X	X	X
Borrower Controls	X	X	X	X
Lender Controls	X	X	X	X
Year FE	X	X	X	X
County FE	X	X	X	X
Lender x County FE	X	X	X	X
Note:				*p<0.1; **p<0.05; ***p<0.01

This table reports the impact of local opioid abuse on the approval rate of individual mortgage applications submitted to banks. *Approval* is an indicator variable for whether a mortgage application was approved. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). $I(LTV > 3)$ is an indicator variable for whether the loan-to-income ratio of the application was greater than 3. County controls include all county control variables reported in Table 1 Panel A. Borrower controls include log income, log mortgage principal, lien status, sex, and minority status. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, county, and lender by county fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 8: Opioid Supply and Interest Rates

	Interest Rate			
	Purchase		Refinancing	
	Small Bank	Large Bank	Small Bank	Large Bank
	(1)	(2)	(3)	(4)
OpioidSupply	-2.441	1.016^{***}	-1.325	1.166^{***}
	(2.457)	(0.322)	(1.920)	(0.289)
County Controls	X	X	X	X
Borrower Controls	X	X	X	X
Lender Controls	X	X	X	X
Month FE	X	X	X	X
County FE	X	X	X	X
Lender x County FE	X	X	X	X
Observations	80,802	253,453	95,749	468,062
Adj. R^2	0.587	0.657	0.553	0.576
F-stat	0.987	9.932	0.477	16.32

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports 2SLS estimates of the impact of opioid abuse on the interest rates charged by lenders for originated mortgages. *InterestRate* is equal to the interest rate in percentage points of an originated mortgage. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). *OpioidSupply* is instrumented by *PurdueMkt* and *Eligiblity*. County controls include all county control variables reported in Table 1 Panel A. Borrower controls include log income, log mortgage principal, lien status, sex, minority status, and binned values of credit score, LTV, DTI, and number of borrowers. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, county, and lender by county fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 9: Opioid Exposure Spillovers and Interest Rates

	Interest Rate			
	Purchase		Refinancing	
	Small Bank	Large Bank	Small Bank	Large Bank
	(1)	(2)	(3)	(4)
OpioidSupply	0.002	−0.00004	0.003	−0.0001
	(0.002)	(0.0001)	(0.005)	(0.0001)
BankExposure	−4.663	1.060***	−7.181	1.232***
	(5.156)	(0.328)	(14.950)	(0.300)
County Controls	X	X	X	X
Borrower Controls	X	X	X	X
Lender Controls	X	X	X	X
Month FE	X	X	X	X
County FE	X	X	X	X
Lender x County FE	X	X	X	X
Observations	80,789	253,410	95,737	467,871
Adj. R^2	0.507	0.656	0.458	0.574
F-stat	0.818	10.41	0.231	16.89

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the spillover effects of exposure to the opioid epidemic on interest rates charged by banks for mortgages. *InterestRate* is equal to the interest rate in percentage points of an originated mortgage. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). *OpioidSupply* is instrumented by *PurdueMkt* and *Eligiblity*. *BankExposure* equals the average county per capita opioid supply in counties where the lender has a branch in, weighted by deposit share. County controls include all county control variables reported in Table 1 Panel A. Borrower controls include log income, log mortgage principal, lien status, sex, minority status, and binned values of credit score, LTV, DTI, and number of borrowers. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, county, and lender by county fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 10: Opioid Abuse and Mortgage Default Rates

	I(90+ days delinquent)			
	Purchase		Refinancing	
	Small Bank	Large Bank	Small Bank	Large Bank
	(1)	(2)	(3)	(4)
OpioidSupply	−0.339	−0.026	−0.273	-0.043^{**}
	(0.437)	(0.048)	(0.313)	(0.021)
County Controls	X	X	X	X
Borrower Controls	X	X	X	X
Lender Controls	X	X	X	X
Month FE	X	X	X	X
County FE	X	X	X	X
Lender x County FE	X	X	X	X
Observations	40,785	127,250	43,927	220,573
Adj. R^2	0.042	0.019	0.039	0.018
F-stat	0.601	0.295	0.571	4.34

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

This table reports the impact of opioid abuse on the default rates of small and large bank originated mortgages. I(90+ days deliquent) is an indicator variable for whether a mortgage has been delinquent in payment for over 90 days. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). *OpioidSupply* is instrumented by $PurdueMkt$ and $Eligiblity$. County controls include all county control variables reported in Table 1 Panel A. Borrower controls include log income, log mortgage principal, lien status, sex, minority status, and binned values of credit score, LTV, DTI, and number of borrowers. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, county, and lender by county fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 11: Opioid Exposure and Portfolio Credit Risk

	Small Bank		Large Bank	
	Charge-offs	Non-performing	Charge-offs	Non-performing
	(1)	(2)	(3)	(4)
BankExposure	-0.002^{***}	0.0008^{*}	0.022^{***}	0.005
	(0.0005)	(0.0005)	(0.011)	(2.768)
Lender Controls	X	X	X	X
Year FE	X	X	X	X
Lender FE	X	X	X	X
Observations	31,393	31,393	378	378
Adj. R^2	0.353	0.432	0.544	0.764
Note:			*p<0.1; **p<0.05; ***p<0.01	

This table reports the impact of national exposure to the opioid epidemic on banks' residential mortgage portfolio credit risk. $Charge-offs$ equals the percentage of mortgages on a bank's balance sheet that are charged-off in a year. $Non-performing$ equals the percentage of mortgages on a bank's balance sheet that become non-performing in a year. *BankExposure* equals the average county per capita opioid supply in counties where the lender has a branch in, weighted by deposit share. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year and lender fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table 12: Opioid Exposure and Shifts in Lending Composition

	% Of Total Assets					
	CommMort	Credit Card	Consumer	C&I	Construction	Agricultural
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Small Banks						
BankExposure	-0.0106***	0.0003	-0.0025*	-0.0034**	-0.0051**	0.0001
	(0.0022)	(0.0002)	(0.0014)	(0.0014)	(0.0023)	(0.0004)
Observations	31,765	31,765	31,765	31,765	31,765	31,765
Adj. R-squared	0.747	0.545	0.877	0.793	0.649	0.957
Panel B: Large Banks						
BankExposure	0.0236	-0.0144**	-0.0203	-0.0207	-0.0006	0.0021
	(0.0167)	(0.0058)	(0.0203)	(0.0269)	(0.0146)	(0.0021)
Observations	381	381	381	381	381	381
Adj. R-squared	0.797	0.992	0.983	0.9	0.825	0.958
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the impact of national exposure to the opioid epidemic on banks' lending activities apart from residential mortgages, scaled by total assets on the bank's balance sheet. Columns (1) through (6) report the results for commercial mortgages, credit card loans, consumer loans, C&I loans, construction loans, and agricultural loans respectively. Panel A reports the results for small banks, while Panel B reports the results for large banks. *BankExposure* equals the average county per capita opioid supply in counties where the lender has a branch in, weighted by deposit share. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year and lender fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

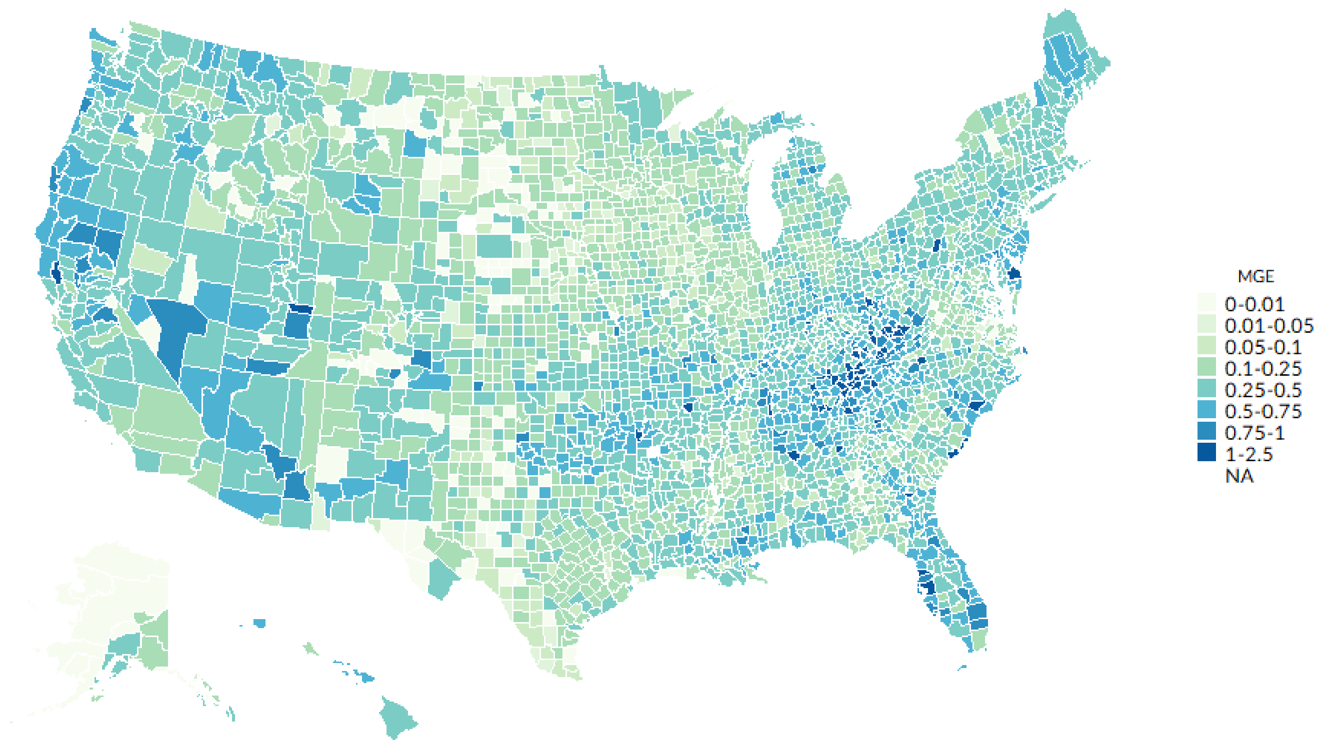
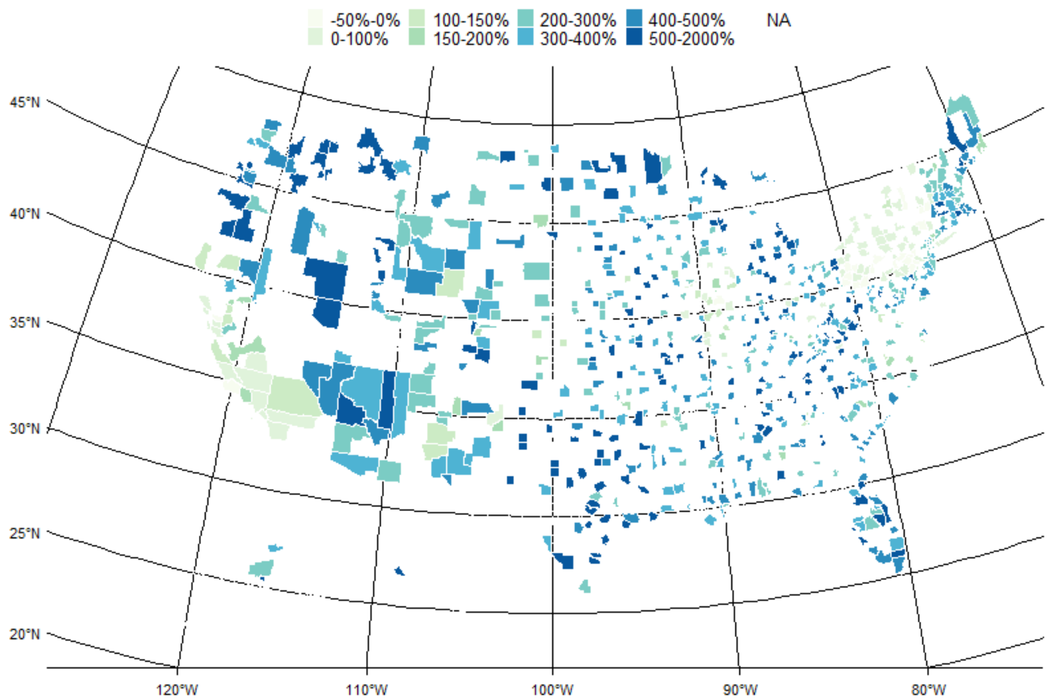
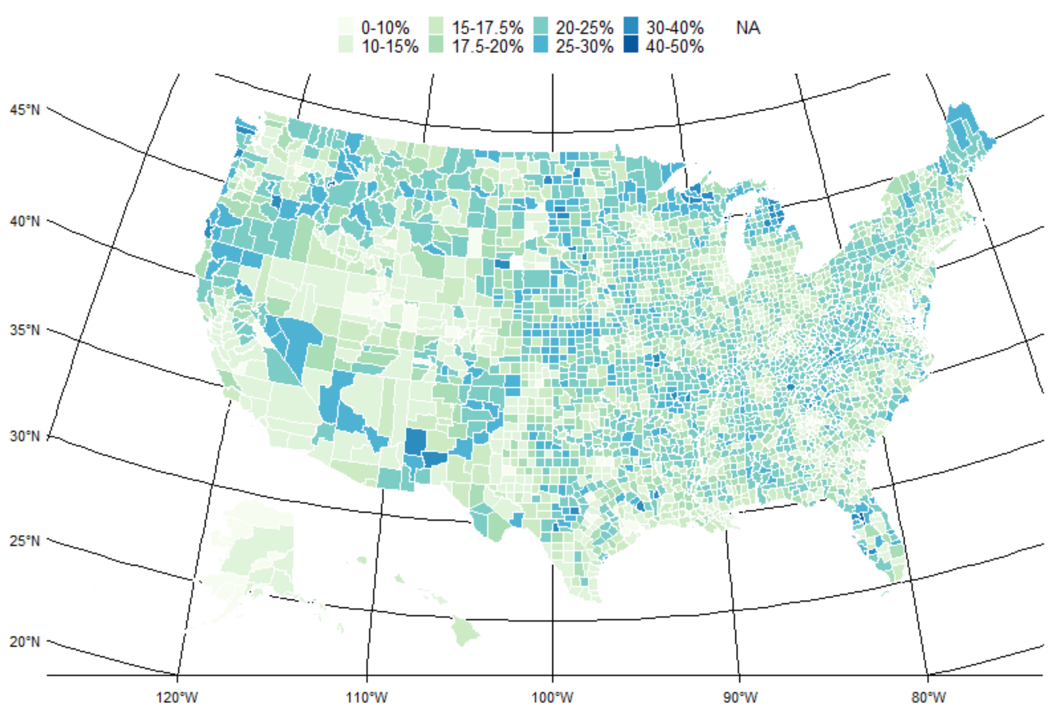


Figure 1: County-Level Opioid Supply Per Capita in the United States



(a) Purdue Marketing



(b) Medicaid Part-D Eligibility Rates

Figure 2: Instrumental Variables

Appendix A. Additional Tables

Table A1: County Opioid Exposure and Aggregate Bank Mortgage Lending

	Log(Mortgage Volume)		
	Bank	Small Bank	Large Bank
	(1)	(2)	(3)
Panel A: All Mortgages			
OpioidSupply	-1.726^{***}	-1.891^{***}	-1.778^{***}
	(0.337)	(0.43)	(0.368)
Adj. R^2	0.931	0.851	0.928
F-stat	26.2	19.35	23.36
Panel B: Purchase Mortgages			
OpioidSupply	-1.743^{***}	-2.110^{***}	-1.849^{***}
	(0.363)	(0.481)	(0.409)
Adj. R^2	0.919	0.807	0.899
F-stat	23.03	19.24	20.47
Panel C: Refinancing Mortgages			
OpioidSupply	-1.879^{***}	-2.028^{***}	-1.790^{***}
	(0.348)	(0.455)	(0.369)
Adj. R^2	0.927	0.833	0.929
F-stat	29.15	19.91	23.5
County Controls	X	X	X
Year FE	X	X	X
State FE	X	X	X
Observations	4,997	4,997	4,997

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the impact of local opioid abuse on total county mortgage lending volume provided by small and large banks. *Log*(Mortgage Volume) equals the log annual dollar volume of all owner occupied single family mortgages originated by bank in a county. Columns (1) through (3) reports the log mortgage volume for all banks, small banks and large banks respectively. *OpioidSupply* is instrumented by *PurdueMkt* and *Eligiblity*. County controls include all county control variables reported in Table 1 Panel A. All regressions include year and state, fixed effects. Standard errors are clustered by county, and are reported in parentheses below coefficient estimates.

Table A2: Local Opioid Supply and Bank Lending Volume - OLS Model

	Log(Mortgage Volume)					
	Small Bank			Large Bank		
	All	Purchase	Refinancing	All	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
OpioidSupply	-0.420^{***}	-0.476^{***}	-0.397^{***}	-0.405^{**}	-0.691^{**}	-0.317
	(0.103)	(0.117)	(0.105)	(0.201)	(0.275)	(0.194)
County Controls	X	X	X	X	X	X
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
County FE	X	X	X	X	X	X
Lender x County FE	X	X	X	X	X	X
Observations	1,013,994	1,013,994	1,013,994	564,865	564,865	564,865
Adj. R^2	0.038	0.049	0.052	0.119	0.144	0.142

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the OLS estimates for the impact of local opioid abuse on mortgage lending volume for small and large banks. *Log*(Mortgage Volume) equals the log annual dollar volume of owner occupied single family mortgages originated by a lender in a county. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). County controls include all county control variables reported in Table 1 Panel A. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, state, and lender by state fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table A3: Opioid Exposure and National Mortgage Lending By Mortgage Specialization

	Log(Total Mortgage Volume)					
	Small Bank			Large Bank		
	All	Purchase	Refinancing	All	Purchase	Refinancing
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mortgage Banks						
BankExposure	-0.513^{**}	-0.869^{***}	-0.360	-0.926	-1.144	-1.214
	(0.210)	(0.313)	(0.293)	(2.768)	(3.722)	(2.713)
Observations	6,647	6,647	6,647	74	74	74
Adj. R^2	0.564	0.588	0.578	0.368	0.450	0.196
Panel B: Non-Mortgage Banks						
BankExposure	-0.491^{***}	-0.314	-0.658^{**}	-2.696	2.183^{*}	-6.632
	(0.167)	(0.197)	(0.183)	(3.089)	(1.25)	(1.953)
Observations	24,258	24,258	24,258	304	304	304
Adj. R^2	0.525	0.565	0.57	0.581	0.715	0.547
Lender Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Lender FE	X	X	X	X	X	X

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports the impact of national exposure to the opioid epidemic on national mortgage lending volume for banks, depending on mortgage specialization. Panel A displays the effect of aggregate opioid exposure on banks specializing in mortgage lending, whil Panel B displays the effect for non-mortgage specialized banks. *Log*(Total Mortgage Lending) log dollar volume of all owner occupied single family mortgages originated by a lender in a year. *BankExposure* equals the average county per capita opioid supply in counties where the lender has a branch in, weighted by deposit share. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year and lender fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Table A4: Opioid Supply and Interest Rates - OLS Results

	Interest Rate			
	Purchase		Refinancing	
	Small Bank	Large Bank	Small Bank	Large Bank
	(1)	(2)	(3)	(4)
OpioidSupply	0.153***	0.031	0.117	0.042**
	(0.053)	(0.019)	(0.081)	(0.018)
County Controls	X	X	X	X
Borrower Controls	X	X	X	X
Lender Controls	X	X	X	X
Month FE	X	X	X	X
County FE	X	X	X	X
Lender x County FE	X	X	X	X
Observations	80,802	253,453	95,749	468,062
Adj. R^2	0.566	0.67	0.558	0.587

Note: *p<0.1; **p<0.05; ***p<0.01

This table reports OLS estimates for the impact of opioid abuse on the interest rates charged by lenders for originated mortgages. *InterestRate* is equal to the interest rate in percentage points of an originated mortgage. *OpioidSupply* equals the county per capita supply of opioids, measured in morphine grams equivalent (MGE). County controls include all county control variables reported in Table 1 Panel A. Borrower controls include log income, log mortgage principal, lien status, sex, minority status, and binned values of credit score, LTV, DTI, and number of borrowers. Lender controls include all bank control variables reported in Table 1 Panel B. All regressions include year, county, and lender by county fixed effects. Standard errors are clustered by lender, and are reported in parentheses below coefficient estimates.

Appendix B. Additional Figures

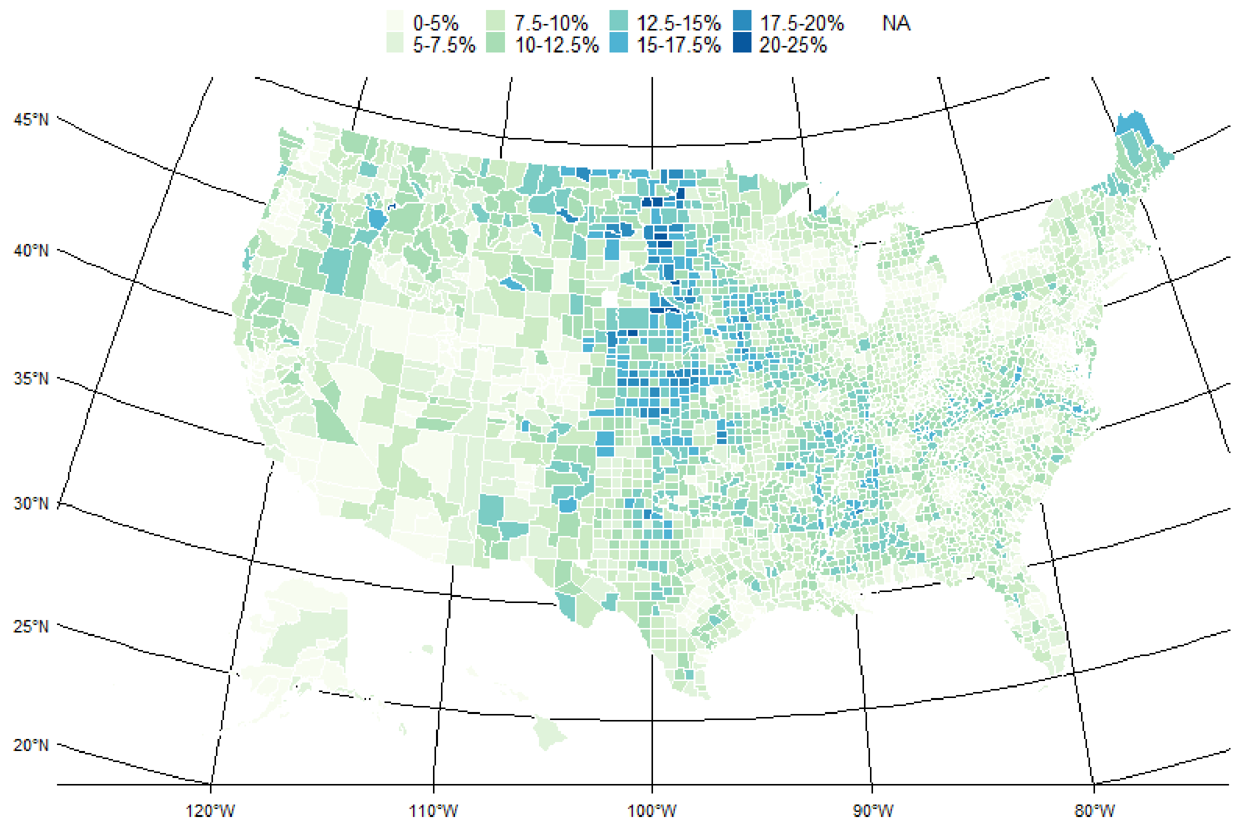


Figure A1: Medicaid Part-D Enrollment Rates