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Real Effects of Financial Conditions: How Does Provider Financial Health Affect Opioid Prescription?

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We examine how healthcare providers' financial health affects their opioid prescription decisions, using changes in house prices in providers' residential neighborhoods as shocks to their wealth. We find that providers increase opioid prescriptions when experiencing adverse financial conditions: a one-standard-deviation decrease in house price growth leads to a 3% increase in opioid prescriptions. Results are robust to including provider office–year fixed effect and using the subsample of providers who live far away from their offices, which largely rules out a patient–demand explanation. Providers living in zip codes with price changes in the bottom half during 2007–2009 increased their opioid prescriptions by approximately 16% more in 2010–2012 than others. The effect is stronger among providers with greater home equity, those in competitive markets, and those serving vulnerable populations. Our findings reveal a previously undocumented channel through which providers' financial incentives affect opioid prescriptions.

JEL Codes: G51, I11, I13, I14, I18, L15, R30

Keywords: Opioid, prescription, healthcare provider, real estate, financial conditions, wealth shock, ethics

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1 Introduction

The rising opioid crisis has become a significant public health concern, with far-reaching consequences for individuals, families, and communities. The COVID-19 pandemic has significantly exacerbated the opioid crisis in the United States, with drug overdose deaths increasing dramatically during and after the pandemic. While numerous factors contribute to this epidemic, understanding the role of healthcare providers in prescribing opioids is crucial, especially given anecdotal evidence of "pill mills". Hence, this study explores a potentially controversial and understudied aspect of the crisis: the effect of doctors' financial pressure on their opioid prescribing patterns.

We find that healthcare providers prescribe more opioids when they experience a relative decline in the price of their house—the largest component of personal wealth for most Americans. This result is estimated relative to the other doctors of similar specialties within the same practice. It is consistent with the idea that, faced with a wealth shock, doctors prescribe more opioids, possibly to ensure repeated patient visits and a steady customer base. This result also implies that economic pressures might influence medical decision-making, potentially at the expense of patient well-being, raising serious ethical questions about the integrity of medical practice. Our findings have important implications for healthcare policy, medical ethics training, and the structure of provider compensation, suggesting that more effective strategies are needed to address the opioid epidemic and other addictions induced by prescription medication.

How do doctors benefit financially from prescribing opioids? First, volume-based compensation is the most common type of base pay for over 80% of primary care doctors and over 90% of specialists at medical practices owned by health systems. When volume-based incentives were included in compensation plans, they accounted for more than two-thirds of providers' compensation. Moreover, increasing the volume of services is the most commonly cited action for providers to increase their compensation, reported by 70% of provider organizations (Reid et al., 2022). This payment model incentivizes providers to maximize the number of patients they see.

In addition, many healthcare facilities (77%) conduct patient satisfaction surveys and some (22%) consider these survey results to set their doctor's pay, according to Schneider et al. (2022). This practice can inadvertently encourage opioid prescriptions, as patients in pain or seeking opioids due to existing addiction are more likely to be satisfied when doctors prescribe opioids, which are stronger painkillers than alternatives for patients in pain. In a study of musculoskeletal pain patients by Sites et al. (2018), patients who receive more opioid prescriptions are more likely to report high satisfaction scores. Carrico et al. (2018) find that 36% of providers who are financially incentivized by these surveys reported that their opioid prescribing practices are also influenced by the reported satisfaction scores.

We use detailed provider–year level Medicare Part D prescription data, matched with house price growth rates at providers' residential ZIP codes. Our sample includes 94,936 providers in all 50 states, spanning from 2010 to 2020. Our analysis yields six main findings. First, we document that providers increase their opioid prescriptions when experiencing negative shocks to their financial health, as measured by house price changes in their residential ZIP codes. The economic magnitude is substantial: a one-standard-deviation decrease in house price growth (approximately 6%) leads providers to prescribe 3% more opioids. This effect is not driven by a general increase in prescriptions—we find that the ratio of opioid to total prescription costs increases when providers face financial stress.

The relationship between house prices and opioid prescriptions exhibits notable time variation. Specifically, the negative effect of house price growth on opioid prescriptions is strongest, at the beginning of our sample, between 2010 and 2015, before diminishing in subsequent years. This pattern likely reflects both the heightened salience of housing wealth during the post-crisis recovery and the introduction of stricter state–level opioid prescription regulations from 2016 onwards.

The Great Financial Crisis of 2007-2009 offers an opportunity to examine how housing wealth shocks influence prescribing behavior. We find that providers living in areas in the bottom half of the housing price declines during 2007-2009 increased their opioid prescriptions by approximately 16% more in 2010–2012 than those in less affected regions. This effect waned after 2012, possibly due to the housing market recovery. These results suggest that financial distress can influence providers' prescribing decisions.

Second, this relationship is stronger among providers with greater home equity, including those without mortgages or with low loan–to–value ratios. These providers demonstrate responses to house price changes that are approximately twice as large as the average effect, consistent with their wealth being more sensitive to housing market fluctuations.

Third, the effect is particularly pronounced in competitive healthcare markets, where it more than doubles in magnitude. This amplification in highly competitive markets suggests that financial pressure may influence prescription behavior more strongly when providers face greater competition for patients.

Fourth, we find stronger effects among providers who graduated from medical school in earlier years, likely before the heightened awareness of the opioid epidemic led to enhanced medical education on prescription practices. This pattern suggests that recent improvements in medical education about opioid risks may help mitigate the influence of financial pressure on prescription decisions.

Fifth, the effects are particularly pronounced among nurse practitioners. Due to their lower incomes relative to physicians, housing typically represents a larger share of their total wealth portfolio. Consistent with our financial motivation hypothesis, relative to other providers, nurse practitioners show five times as large responses to housing market changes when making prescribing decisions.

Sixth, we find that the relationship between providers' financial stress and opioid prescriptions is stronger among providers serving more vulnerable populations. Specifically, providers with higher proportions of high-health risk patients or Black patients, as well as those serving in low-income or low-education ZIP codes show substantially larger increases in opioid prescriptions when experiencing financial pressure. These findings suggest that the adverse effects of provider financial stress may disproportionately affect patient populations that are already more vulnerable to opioid-related complications.

Our findings have several important implications for healthcare policy and the ongoing opioid crisis. First, they reveal a previously undocumented channel through which economic conditions can affect opioid prescription patterns: providers' personal financial circumstances. While existing research has primarily focused on patient-side economic factors or broad regulatory changes, our results suggest that providers' financial stress can meaningfully influence their prescription decisions.

Moreover, the heterogeneous effects we document raise additional policy concerns. The amplification of the effect in competitive healthcare markets suggests that market pressures may sometimes work against public health interests. While competition in healthcare markets is generally thought to benefit patients through lower prices and improved quality of care, our findings indicate that it might also create incentives for providers under financial stress to prescribe more opioids, potentially as a way to maintain patient relationships. This tension between market competition and provider behavior deserves careful consideration in healthcare policy design.

In addition, the large effects among earlier medical school graduates point to the potential value of continuing medical education. While recent improvements in medical school curricula regarding opioid prescription appear to have some protective effect, our results suggest that targeted interventions may be needed for providers who completed their training before these educational reforms. Mandatory continuing education programs specifically focused on opioid prescription practices could help mitigate the influence of financial pressures on prescription decisions.

Finally, the stronger effects among providers serving high-health risk and Black patients or low-income and low-education communities suggest that financial stress may exacerbate existing healthcare disparities. These results are particularly concerning given the recent acceleration in opioid overdose deaths among Black Americans. They indicate that policies aimed at addressing the opioid crisis may need to pay special attention to vulnerable populations and the providers who serve them.

1.1 Contribution to the Literature

Our paper makes several important contributions to the literature. First, we contribute to a small literature examining the relationship between healthcare providers' financial incentives and their opioid prescribing behaviors. A few studies[1] reveal that providers who received payments from pharmaceutical companies were more likely to prescribe opioids. We contribute by offering the new insight that personal financial conditions can affect opioid prescriptions, while the other two studies focus on financial incentives. In addition, our analyses support a causal interpretation, while the other studies document correlations.

Several studies have examined policy interventions aimed at healthcare providers in order to reduce abuse in opioid prescription. Buchmueller and Carey (2018) find that when providers are required to check prescribing histories, they significantly reduce opioid prescription. Sacarny et al. (2017) describe letter interventions targeting high-volume prescribers. Lastly, Popovici et al. (2018) document that doctor shopping laws can reduce prescription opioid overdose deaths and treatment admissions. Larkin et al. (2020) find that banning sales representatives from directly marketing to doctors lowers opioid prescription.

Our paper also contributes to the the literature on how their financial constraints affect health care providers' quality of service in general. For example, Aghamolla et al. (2024)

[1]See, Hadland et al. (2018), Hadland et al. (2019), Fleischman et al. (2019), Hollander et al. (2020), Zezza and Bachhuber (2018), Inoue et al. (2020), Lee et al. (2019), Vogel (2019), Nguyen et al. (2019a) and Nguyen et al. (2019b).

show that shocks to credit availability, due to their lender banks being subject to stress tests, worsens health outcomes at hospitals. There are also papers (e.g., Adelino et al. (2015) and Gao et al. (2024)) on how changes in financial conditions affect investment and operations of nonprofit hospitals.

There is also a strand of literature using real estate shocks to measure individuals' financial stress and the effect of these shocks on their consumption (Aladangady (2017) and Berger et al. (2017)), labor market decisions (e.g., Bernstein (2021)), risk taking (e.g., Pool et al. (2019)), as well as misconduct, which is the most relevant to our study (e.g., Dimmock et al. (2021)). In this paper, we explore whether this effect can reach to extremes: whether shocks to one's personal wealth can affect the physical health of others and contribute to "the worst drug epidemic in US history." Specifically, we study whether shocks to medical doctors' personal wealth affect their prescription of opioids to patients.

2 Opioid Crisis in The U.S.

The opioid crisis in the United States has evolved through multiple waves since the 1990s, resulting in a devastating public health catastrophe (Dasgupta et al., 2018; Kolodny et al., 2015). The crisis began with the increased marketing and prescribing of opioid painkillers, particularly OxyContin, leading to a surge in opioid use and misuse (Dasgupta et al., 2018). The prescription opioid sales quadrupled between 1999 and 2008.[2] Between 2001 and 2016, opioid-related deaths increased by 292%, from 33.3 to 130.7 deaths per million population (Gomes et al., 2018).

The economic and social impact of the opioid crisis has been staggering. In 2017 alone, the economic cost of opioid use disorder and overdose deaths was estimated at nearly $1.02 trillion (Florence et al., 2021). The crisis has led to decreased life expectancy in the United States, with more than 130 Americans dying each day from opioid overdoses

[2] See, https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6043a4.htm.

in 2017.[3] Then the COVID-19 pandemic has significantly exacerbated the opioid crisis in the United States, with drug overdose deaths increasing dramatically during and after the pandemic. According to CDC data, opioid overdose deaths increased by 38% nationally in 2020.[4] Opioids also have a significant effect on economic activities. Ouimet et al. (2023) find that opioid prescriptions reduce employment and establishment growth.

The large role of prescription opioids in the opioid crisis is demonstrated by the wave of litigation against pharmaceutical manufacturers and distributors. State attorneys general filed lawsuits against drug companies, distributors, and pharmacy chains, seeking accountability for their alleged roles in the epidemic. These legal actions have yielded substantial settlements, with funds now flowing to states for addiction treatment and prevention programs. The most notable case involved Purdue Pharma, maker of OxyContin, which agreed to a landmark settlement potentially worth $12 billion with 23 states and roughly 2,000 local governments - though the company's bankruptcy and restructuring have complicated the final resolution.[5] Other major settlements include a $26 billion agreement with Johnson & Johnson and three major pharmaceutical distributors - AmerisourceBergen, Cardinal Health, and McKesson.[6] Additionally, pharmacy chains such as CVS, Walgreens, and Walmart have agreed to pay a combined $13 billion to resolve lawsuits claiming they contributed to the opioid epidemic.[7] The funds from these settlements are now being distributed to states and local governments to support opioid treatment, prevention, and recovery programs.[8]

Given the proven effects of supply-side factors on the opioid crisis, states established Prescription Drug Monitoring Programs (PDMPs) to curb the misuse of opioid prescriptions. These programs create databases on patients' current or past use of controlled

[3] See, `https://www.hrsa.gov/opioids`.
[4] See, `https://www.osc.ny.gov/reports/continuing-crisis-drug-overdose-deaths-new-york`.
[5] See, `https://www.americanbar.org/news/abanews/aba-news-archives/2019/09/opioid-lawsuits-generate-payouts-controversy/`.
[6] See, `https://www.naag.org/issues/opioids/`.
[7] See, `https://www.bmj.com/content/379/bmj.o2688`.
[8] See, `https://ag.ny.gov/nys-opioid-settlement`.

substances. Access to this database before prescribing opioids for medical doctors was voluntary at first. However, observing voluntary access led to a small fraction of providers accessing the information, between 2012-2017 16 states shifted to a must-access system. Additionally, states began enacting prescribing cap laws, limiting the dosage and duration of opioid prescriptions. Some states also introduced "pill mill" laws to regulate pain management clinics and combat inappropriate prescribing practices. Furthermore, many states require prescribers to complete mandatory education on pain management and addiction. By 2019, 33 states had mandatory PDMP query laws, 11 passed pill mill laws, and 35 enacted prescribing cap laws (Stone et al., 2020). However, drug overdose deaths, significant fraction of which involve prescribed opioids, remain a leading cause of injury mortality in the U.S. (Centers for Disease Control and Prevention, 2023).

3 Data and Sample

This section first describes the data sources used in the study and how we construct the sample. We then present the demographics and the property characteristics of the providers, and their prescriptions of opioid drugs.

3.1 Provider Demographics

We obtain healthcare providers' demographic information from the National Plan and Provider Enumeration System (NPPES) managed by the Centers for Medicare and Medicaid Services (CMS). In the U.S., healthcare providers are required to obtain a unique National Provider Identifier (NPI) issued by the CMS, as mandated by the Health Insurance Portability and Accountability Act of 1996 (HIPAA).[9] CMS has developed the NPPES to assign these unique identifiers. Once assigned, an NPI remains the same, even if the

[9]Specifically, entities (individuals or organizations) who receive payment for health care in the normal course of business and exchange health care data (e.g., claims) electronically are covered by the HIPAA, and are required to obtain an NPI.

provider has a change of name, address, or other information. In September 2007, CMS began disclosing NPPES health care provider data that are disclosable under the Freedom of Information Act (FOIA) to the public.[10] The data are updated monthly and cover both the active and deactivated providers. Importantly, healthcare providers with active NPIs cannot opt out or ask to suppress their record data. We obtain the monthly downloadable files between January 2007 and March 2023 to construct panel data for providers. The data contain information on the provider's NPI, first/middle/last name, gender, taxonomy group, practice location address, and mailing address. We supplement the NPPES data with the Physician Compare data provided by the CMS to get additional information on the provider's medical school and graduation year.[11] We then geolocate providers' practice location addresses to get the latitudes and longitudes, and the identifier for the practice address (Placekey).[12]

3.2 Property Information

We obtain a national database of property tax and deed records from CoreLogic, a premier real estate and mortgage transaction data provider. The deed records cover the near-universe of housing transactions starting from the 1990s,[13] with more than 850 million historical real estate transactions from over 3,000 County Clerk/Recorder offices. Our version of the data was extracted in February 2021. The data provide important information on the address of the property, buyer and seller names, transaction date and price, mortgage information (amount, term, and interest rate), and other property characteristics.

[10] In accordance with the e-FOIA Amendments, CMS has disclosed NPPES Downloadable files via the Internet starting June 18, 2018. More information about the NPPES data can be found here: `https://www.cms.gov/medicare/regulations-guidance/administrative-simplification/data-dissemination`.

[11] The data is downloaded from `https://data.nber.org/data/cms-physician-compare-data.html`. We accessed the latest version of this data, which was updated on 2018-02-28. Providers registered later than this date are not covered.

[12] More information about Placekey can be found here `https://www.placekey.io/`.

[13] According to Bernstein et al. (2021), "CoreLogic's coverage start dates vary by state, with high-quality coverage beginning in the late 1980s for some states, such as California, Massachusetts, and Illinois, and in the early to mid-1990s for other states."

Moreover, CoreLogic has processed the data to generate valuable information like parsing names into first/middle/last names and geolocating the addresses to get the latitude and longitude of the property.

CoreLogic data has been widely used in the literature to identify properties of individuals –e.g., of patent innovators and equity analysts (Bernstein et al., 2021; Aslan, 2022). We match the NPPES data with the CoreLogic data to identify a provider's properties. Specifically, we match based on the provider's name and calculate the distance between the provider's practice location and the property using the latitudes and longitudes of the addresses. We keep that providers live within 50 kilometers of their workplaces to further improve the matching. Finally, we construct panel data of the provider's property ownership at the annual frequency. Specifically, we consider the provider owns a certain property in a year, if the property was purchased before this year, and the property was not sold this year. When the purchase or sale date is missing, we check whether the provider pays property tax for the property in a year to decide the ownership.

We get the ZIP code level Zillow Home Value Index (ZHVI) at the monthly frequency from Zillow. This data is available to us from January 2001 till the end of July 2022. This data has been widely used in the literature to capture housing price shocks to individuals' properties (Dimmock et al., 2021; Carvalho et al., 2023).

3.3 Opioid Prescriptions

We get the provider's prescription information from Medicare Part D. The data cover information on prescription drugs to Medicare beneficiaries enrolled in Part D (Prescription Drug Coverage), who comprise approximately 76% of the total Medicare population (CMS, 2022). Specifically, we use the Medicare Part D Prescribers by Provider dataset from CMS to get individual healthcare provider's prescription behavior. This data is aggregated at the provider-year level and has been available since 2013. Since our version of CoreLogic data is only available till 2021 February, we end our sample period in 2020.

The Part D data contains overall drug and Opioid drug utilization (claims and day's supply), drug costs, and beneficiary counts aggregated by provider and year. In addition, beneficiary demographic and health characteristics are provided which include age, sex, race, and risk scores.

To protect the privacy of Medicare beneficiaries, the drug prescription quantity (beneficiary count) is suppressed if the number of claims (beneficiaries) is between 1 and 10. We define observations with suppressed values as missing in our analysis, and these observations will be dropped automatically. We then define a dummy variable (*Opioid Dummy*) indicating whether the provider prescribes Opioid drugs, and set it equal to 1 if the Opioid drug prescription quantity is suppressed or larger than 0. Analysis using *Opioid Dummy* includes all the observations.[14]

We further get the 2010 to 2012 Part D data from ProPublica, a nonprofit investigative journalism organization, which obtained Medicare Part D data from the CMS under the FOIA.[15] The data is at the provider-year-drug level, and we use the Medicare Part D Opioid drug list provided by CMS to aggregate the data to get the provider's Opioid prescription information. However, the ProPublica data only report providers with more than 10 Opioid claims in a year and do not contain information on beneficiary count or beneficiary demographic and health characteristics.[16]

3.4 Sample

We have the following data filtering steps in sampling providers. We start with the combined Medicare Part D data. We first filter the data by medical specialties. Specifically, we drop medical specialties with less than 1,000 providers, specialties associated with

[14]CMS suggested that users may assign an imputed value of their choosing, e.g. five (5), for the suppressed value. Our results are robust to this alternative treatment of the suppressed values.

[15]See: How We Analyzed Medicare's Drug Data (ProPublica, 2013).

[16]Our results are robust to only using the CMS Part D data between 2013 and 2020.

hospital care,[17] or specialties indicating the provider is a student participating in an Organized Health Care Education/Training Program. We then further drop providers of the following specialties: hospice, oncology, urology, obstetrics and gynecology, optometrist, dermatology, dentist, ophthalmology, advanced practice midwife, and radiology. This step drops 16% of our initial sample observations. Then we drop providers who work within hospitals. Specifically, we drop providers whose practice location addresses include the keywords hospital, emergency, or urgent, and also drop providers whose addresses can be matched to hospital addresses in the Healthcare Cost Report Information System (HCRIS) data, provided by CMS. This step drops an additional 22% of our sample observations. The last step keeps the practice location ZIP code-medical specialty pairs with multiple providers during the sample period, which drops an additional 47% of our sample observations. This ensures that we have variations within the fixed effects used in our specification.

Finally, we merge the Part D data with CoreLogic data to get providers' property information, and then merge with Zillow data to get information on the housing price growth rate at the ZIP code of the property. In this sample, we have 77% of the observations with providers having only one property, 17% having two, 5% having three, and 1% having more than three. We aggregate the data by taking the simple average housing price growth rate for providers with multiple properties, so that we have one observation for each provider-year pair.[18] Our final sample includes 99,813 providers practicing in 11,114 ZIP codes, covering the 2010 to 2020 time periods.

3.5 Descriptive Statistics

Table 1 reports the summary statistics for the main variables used in our analysis. Healthcare providers' residential ZIP codes, on average, experience a 3% housing price growth

[17] Specifically, we drop specialties containing the following keywords: surgery, anesthesia, emergency, otorhinolaryngology, critical care, podiatry, or hospital.

[18] Our results are robust to including all properties of the provider and treat them as separate observations.

rate (in log differences). There are significant variations in housing price growth rates, with a standard deviation of 6%. On average, providers in our sample are prescribing drugs 24 years after graduation. 11% of the sample providers are nurse practitioners, and 27% of the providers have no remaining mortgage balance for their properties. The average distance between providers' home and their offices is around 12 kilometers.

Regarding providers' prescription of opioid drugs, on average, a provider's annual prescription of opioid drugs costs $9,186, aggregating to 5,188 days of supply and 219 claims, to 55 recipients. The opioid drug cost accounts for 6% of all drugs prescribed by the same provider.

4 Effects of Provider Financial Health on Opioid Prescription

4.1 Main Results

To test whether healthcare providers' financial conditions affect the amount of opioids they prescribe, we run the following regression:

$$Opioid\ Prescriptions_{p,t} = \beta Home\ Price\ Growth_{z,t-1} + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \tag{1}$$

where p indexes the provider, z the ZIP code of the provider's home address, l the location as identified by city or ZIP code level of their work address, and t the year. Our main independent variable is the annual growth rate of house prices in the provider's residential ZIP code (z), calculated as the log difference between consecutive years: $Log(HPI_{z,t-1} - HPI_{z,t-2})$.

We examine various dependent variables, all measured at the provider–year level. The first dependent variable, *Log Opioid Cost*, is the natural logarithm of one plus the cost of opioid prescribed. The second, *Log Opioid Days Supply*, is the natural logarithm of one plus total days of opioid supply. Our third dependent variable, *Log Opioid Claims,* is the natural logarithm of one plus the number of opioid prescriptions.The fourth dependent variable, *Log Opioid Recipient #*, is the natural logarithm of one plus the number of patients receiving opioid prescriptions.[19] The sample period is between 2010 and 2020, as explained in the Data section.

Table 2 presents our main findings. We control for provider fixed effects in both panels. In addition, Panel A adds city–year fixed effects, while Panel B adds ZIP code-year fixed effects, both based on providers' work location. We correct for the clustering of observations at the provider level. We refer to Column (1) of Panel A as our benchmark specification.

In both panels, the estimated coefficients on *Provider House Price Growth* are negative and statistically different from zero, mostly at the 1% level. The magnitudes are also economically meaningful. According to Column (1), when a provider experiences a one-standard-deviation slower house price growth, approximately by 6% lower, she prescribes 3% (=0.06×0.5) more opioids in terms of total costs. The magnitudes are very similar for opioid days of supply, while smaller for the number of claims, suggesting higher quantities per prescription when providers home price growth is lower. We confirm this finding in untabulated results. According to Column (4), the same reduction in house price growth is associated with 1.2% (=0.06×0.2) increase in the number of patients receiving opioids.[20]

Figure 1 presents a binscatter plot depicting the relationship between *Log Cost* and *Provider Home Price Growth*, after removing provider and office city–year fixed effects. The visual evidence reveals a negative relationship between these variables, corroborating our regression findings.

We then estimate the coefficients on *Provider House Price Growth* for each year of our

[19]Because we exclude providers who never prescribed any opioids in the entire sample, the average probability of a provider prescribing opioid is 94%, which means the raw numbers of opioid costs, claims, days supply, and recipient counts are only zero in around 6% of the observations. This minimizes the econometric concerns raised by Cohn et al. (2022) regarding count data analysis.

[20]The smaller effect on recipient numbers is partly due to the variable being unavailable before 2013. If we estimate Column (1) of Panel A using the same sample, our estimated coefficient decreases by 25% to -0.374. Additional analysis shows no significant relationship between home price growth and opioid cost per recipient.

sample, using the following specification.

$$Log(Opioid\ Cost)_{p,t} = \sum_t \beta_t \times Home\ Price\ Growth_{z,t-1} \times 1(Year)_t + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \quad (2)$$

Figure 2 plots the estimates for β_t, the year-by-year effect of provider house price growth on opioid prescriptions. The effect is strongest in the earlier years of our sample, with negative and statistically significant coefficients between 2010 and 2015, before becoming insignificant from 2016 onwards. Two reasons can explain this. One is the heightened attention to housing wealth in the years following the Great Financial Crisis when house prices were recovering. The other reason is the wave of various state laws and regulations enacted between 2017 and 2019 that imposed stricter controls on opioid prescriptions.

4.2 Effect of Large Price Drops During 2007–2009

The Great Financial Crisis (GFC) of 2007-2009 provides a unique opportunity to study how severe housing wealth shocks affect prescribing behavior. Our prescription data start in 2010, so the earliest house price change we use is the one from the beginning to the end of 2009. To exploit the historical house price shock during the Crisis, we estimate the following specification.

$$Log(Opioid\ Cost)_{p,t} = \sum_t \beta_t \times 1(Large\ Price\ Drop\ in\ GFC)_p \times 1(Year)_t + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \quad (3)$$

1(Large Price Drop in GFC) indicates providers living in ZIP codes that experienced housing price index change in the bottom half during 2007–2009. In this group, the house price index change during 2007–2009 has a mean and median of -27% and -34%, respectively. We interact this indicator with year dummies, *1(Year)*, to trace out the dynamic impact of large house price shocks during the GFC. We include provider fixed effects and office city–year fixed effects.

Figure 3 plots the coefficients β_t and the 90% confidence intervals. The coefficients are positive and statistically significant in 2010 and 2011. The magnitudes suggest that providers living in ZIP codes hit hardest by the GFC increased their opioid prescriptions by approximately 16% more opioids in 2010–2012 compared to those in less affected areas. The effect diminishes and becomes statistically insignificant after 2012, which is potentially associated with house price recoveries in previously hard-hit areas. These results suggest that financial distress can lead providers to prescribe more opioids.

4.3 Robustness

In Table 3, we conduct a suite of robustness tests. A natural question is whether our results reflect a general increase in medication prescriptions, rather than a specific increase in opioid prescriptions, when providers experience low house price growth. We find that indeed the prescription of non-opioid drugs is negatively associated with providers' home price growth rate. We find that non-opioid drug prescriptions are indeed negatively associated with providers' home price growth rate, possibly because prescribing medication offers an expedient way to address patient desires for efficient treatment solutions. We investigate whether this relationship is particularly pronounced for opioids.

In Column (2), we examine this by using as our dependent variable, the ratio of providers' opioid prescription costs to their total prescription costs. The coefficient on *Provider Home Price Growth* remains negative and statistically significant, suggesting a disproportionate larger effect for opioid prescriptions. The economic magnitude is meaningful: a one-standard-deviation decrease in *Provider Home Price Growth* corresponds to a 2% increase relative to the average ratio of opioid costs to total drug costs.

Long-acting opioid drugs, while still carrying addiction risks, generally pose a lower threat of patient addiction compared to their short-acting counterparts. If low providers' home price growth only increases their prescription of long-acting opioid drugs, the negative consequences are less severe. In Column (3), we replace the outcome variable with the natural log of one plus the cost of short-acting opioid drugs. The estimated effect closely mirrors our main results, indicating that providers experiencing slower wealth growth increase prescriptions of more addictive short-acting opioids, posing substantial risks for patient addiction.

A potential concern with our analysis is that providers' home price growth might be correlated with their patients' financial health. Despite our inclusion of office ZIP code-year fixed effects, providers may disproportionately serve patients from their residential neighborhoods. As a result, *Provider Home Price Growth* can be correlated with patients' home price growth. To address this concern, Column (4) repeats our benchmark specification using a subsample of providers whose home-to-office distance exceeds the median. The estimated coefficient on *Provider Home Price Growth* is slightly larger than in our benchmark result. This finding, derived from a sample where providers are less likely to treat their residential neighbors, provides strong evidence against the alternative explanation that our results merely reflect patients' economic conditions.

In Column (5), we further address endogeneity concerns by employing an even more stringent specification that replaces location-year fixed effects with provider office-year fixed effects. This approach effectively compares among providers working in the same office during the same year, essentially controls for patient population characteristics at the office-year level. The coefficient on *Provider Home Price Growth* remains similar in magnitude to our benchmark estimate. The persistence of our results in this specification suggests that our findings are unlikely driven by endogenous patient demand for opioids.

5 Heterogeneity in Effects of Provider Financial Health on Opioid Prescription

In this section, we examine heterogeneous effects across providers through several hypothesis tests. Our analysis employs the following specification:

$$\begin{aligned} Opioid\ Prescriptions_{p,t} =& \beta_1 Home\ Price\ Growth_{z,t-1} \times Indicator_{p(,t)} + \\ & \beta_2 Home\ Price\ Growth_{i,t-1} + \beta_3 Indicator_{p(,t)} + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \end{aligned} \tag{4}$$

where p denotes the provide, z the provider's home ZIP, l the office city or ZIP code, and t the year. We estimate two variants of this specification, alternating between office city–year and office ZIP–year fixed effects, while maintaining provider fixed effects throughout. The *Indicator* represents a binary variable specific to each hypothesis tested in the following analysis.

5.1 Stronger Effects When Providers Have More Home Equity

Our earlier findings indicate that providers increase opioid prescriptions when experiencing relatively low home price growth. If financial health indeed drives this relationship, we would expect the effect to be more pronounced among providers with greater home equity, as their wealth is more sensitive to house price fluctuations. We examine this hypothesis in Table 4.

CoreLogic data provide the purchase price of the property, and information on the mortgage related to the purchase, i.e., mortgage amount, mortgage term (in months), and mortgage rate. This information allows us to calculate the remaining mortgage balance after t months using the following formula.

$$Balance_t = Amount \times [(1 + Rate/12)^{Term} - (1 + Rate)^t]/[(1 + Rate/12)^{Term} - 1]$$

If the purchase price of the property is missing, we use the ZHVI of the property's zip code at the purchase month. If the mortgage rate is missing, we use Freddie Mac's Primary Mortgage Market Survey (PMMS) rate of the week at the mortgage origination with the same mortgage term.[21] We then update the property value every year based on the purchase price and housing price growth rate of the property's ZIP code. With property value, we are able to construct the year-end loan-to-value ratio. For providers who are not carrying mortgages when they purchase the property, the mortgage balances and the loan-to-value rations are defined as zero.

Columns (1) and (2) estimate Equation 4 with the *Indicator* being *No Mortgage*, which equals one for providers without mortgages and zero otherwise. Columns (3) and (4) employ an alternative specification where the *Indicator* is *Low LTV*, which equals one if the provider's loan-to-value ratio falls in the bottom quintile. All specifications include provider fixed effects, with Columns (1) and (3) incorporating office city–year fixed effects and Columns (2) and (4) employing the more granular office ZIP–year fixed effects.

The estimated coefficients on both interaction terms are negative and statistically significant, indicating that providers with greater home equity exhibit heightened sensitivity to house price changes in their prescription behavior. The magnitude of these effects is substantial: providers with high home equity demonstrate a response to house price changes that is around twice larger than the average effect in our benchmark specification. These findings strengthen our interpretation that providers' financial circumstances materially influence their opioid prescription patterns. In untabulated results, we find that our re-

[21] Freddie Mac provides weekly PMMS rares by surveying lenders on the rates and points for their most popular 30-year fixed-rate, 15-year fixed-rate and 5/1 hybrid amortizing adjustable-rate mortgage products. The survey is based on first-lien prime conventional conforming home purchase mortgages with a loan-to-value of 80 percent.

sults are robust to using a subsample of providers carrying mortgages when purchasing the properties.

5.2 Stronger Effects When Providers Face More Competition

Our interpretation of the main results rests on the premise that providers experiencing financial stress may attempt to strengthen patient retention by prescribing opioids. Under this interpretation, the effect of providers' financial health should be more pronounced in markets with greater competition for patients. We investigate this hypothesis in Table 5.

To measure market competition, we construct a Herfindahl-Hirschman Index (HHI) at the city–year level using the total Part D beneficiaries of the providers in our sample. We then estimate Equation 4, defining our *Indicator* variable as *High Competition*, which equals one for cities in the lowest HHI quintile for that year.

Column (1) includes provider and office city–year fixed effects. The estimated coefficient on the interaction term is -0.63, while the coefficient on the standalone *Provider Home Price Growth* is -0.36. These estimates indicate that the effect of house price changes on prescribing behavior more than doubles in highly competitive markets. Column (2), employing the more granular office ZIP–year fixed effects, yields similar results.

5.3 Stronger Effects Among Older Providers

As the opioid epidemic has gained prominence in academic and policy discussions, medical schools have enhanced their curriculum regarding opioid prescription practices to address addiction risks. Consequently, we hypothesize that providers' financial conditions may have a stronger influence on prescription behavior among those who completed their medical education in earlier years. We test this hypothesis in Table 6.

We estimate Equation 4 with the *Indicator* being *Graduated Earlier*, which equals one for providers whose medical school graduation year falls in the bottom quintile. Column

(1) includes provider and office city–year fixed effects. The estimated coefficient on the interaction term is -1.4 and statistically significant, while that on *Provider Home Price Growth* is 0.1 but statistically indistinguishable from zero. This result suggests that among earlier graduates, a one-standard-deviation decrease in *Provider Home Price Growth* is associated with 7.8% increase in opioid prescription. Column (2), which employs office ZIP–year fixed effects, produces comparable estimates.

5.4 Stronger Effects Among Nurse Practitioners

If financial considerations drive providers' opioid prescribing behavior, we should observe stronger effects among those whose wealth is more concentrated in housing. We test this hypothesis by examining nurse practitioners, who comprise 10% of our sample and typically earn less than physicians. Due to their lower incomes, housing wealth likely represents a larger share of their total wealth portfolio.

To test this hypothesis, we estimate Equation 4, defining the *Indicator* variable as a dummy variable for *Nurse Practitioner*. We exclude Georgia and Oklahoma, as these states prohibit nurse practitioners from prescribing medications with high abuse potential.[22]

The results in Table 7 support our hypothesis. The coefficients on *Provider House Price Growth* are negative and statistically significant in both columns, suggesting the effect is stronger among nurse practitioners. When providers experience a one standard deviation relative decline in house price growth, nurse practitioners increase their opioid prescriptions by 11.8% (=(1.65+0.31)×0.06)—more than five times the 1.9% increase (=0.31×0.06) observed among other providers. This stark difference in sensitivity to housing wealth shocks provides evidence that financial considerations influence prescribing behavior.

[22]See, `https://nursejournal.org/articles/nurse-practitioner-prescriptive-authority-by-state/`.

5.5 Stronger Effects among Providers with More High-Risk or Minority Patients

The increased opioid prescriptions due to providers' slower wealth growth are particularly concerning if they disproportionately affect vulnerable patient populations who face higher risks of addiction or adverse outcomes. While we lack individual patient data, we have data on provider-level patient characteristics, including the average Hierarchical Condition Category (HCC) risk score of their Medicare patients. This risk measure, which predicts expected fee-for-service spending based on patient characteristics, serves as a proxy for patient health status, with higher scores indicating greater expected medical service utilization and poorer health.

In Column (1) of Table 8, we examine whether providers serving higher-risk patients show stronger responses to home price changes in their prescription behavior. We estimate Equation 4 with the *Indicator* being *More High-Risk Patients*, which equals one for providers whose average patient risk score exceeds the median.

Since 2010, Black Americans have experienced a disproportionate increase in opioid overdose deaths compared to other racial groups (Barnett and Meara 2023). We investigate whether providers' financial circumstances differentially affect prescriptions to Black patients. Using Medicare Part D data, we calculate the share of each provider's beneficiaries that are Black. In Column (2), we estimate Equation 4 with the *Indicator* being *More Black Patients*, which equals one for providers in the top quartile of Black patient share.

Prior research has established that individuals with lower income and education levels face higher risks of opioid addiction and overdose deaths.[23] We next examine whether providers practicing in places with lower income or education levels respond more strongly to their own financial conditions. We measure income and education levels at the office ZIP code level, using 2012 ACS 5-year data.

[23] See, Altekruse et al. (2020), Friedman et al. (2019), Nestvold et al. (2023), Office of the Assistant Secretary for Planning and Evaluation (2018), and Centers for Disease Control and Prevention (2022).

In Column (3), we estimate Equation 4 with the *Indicator* being *ZIP Low Income*, which equals one for office ZIP codes in the bottom quintile of household median income. Column (4) replaces the *Indicator* with *ZIP Low Education*, denoting office ZIP codes where the share of residents with bachelor's degrees or higher falls in the bottom quintile.

The estimated coefficients on the interaction term are negative and statistically significant in all four columns. The results suggest that when experiencing slow house price growth, providers increase opioid prescriptions by more if they serve more high-risk, Black, low-income, or low-education patients. Take providers practicing in low-income ZIP codes as an example, their opioid prescription response to their house price growth is 2.6 times larger than providers in other areas.

Notably, the coefficient on the standalone term, *More High-Risk Patients*, is positive and statistically significant. The magnitude indicates that providers with more high-risk patients prescribe 1.2% more opioids relative to the average. This suggests high-risk patients are more susceptible to opioid prescription. The results in this section indicate that the adverse effect of providers' slower wealth growth falls disproportionately on less vulnerable patients, who are already more susceptible to opioid prescription or addiction.

6 Conclusion

This paper documents that healthcare providers' financial circumstances influence their opioid prescription decisions. Using house price changes in providers' residential ZIP codes as a shock to their wealth, we find that providers increase opioid prescriptions when experiencing adverse financial conditions. A one-standard-deviation lower house price growth leads to a 3% increase in opioid prescriptions. Consistent with our baseline result, providers living in zip codes with bottom-half price changes during 2007–2009 increased their opioid prescriptions by approximately 16% more in 2010–2012 than others.

Several patterns in our data suggest a causal interpretation of these findings and illuminate the underlying mechanism. The effect is stronger for providers with greater home equity, consistent with house price changes having larger wealth effects for these providers. The relationship intensifies in more competitive healthcare markets, suggesting that providers may use opioid prescriptions as a tool for patient retention when experiencing slower growth in personal wealth. We also find larger effects among providers who graduated from medical school earlier, likely before the opioid crisis gained widespread attention, indicating that recent improvements in medical education about opioid risks may help mitigate the influence of financial pressure on prescription decisions. The effects are also stronger among nurse practitioners, whose total wealth is more affected by the value of their properties due to their lower incomes relative to physicians.

Particularly concerning is our finding that the relationship between providers' financial stress and opioid prescriptions is stronger among providers serving vulnerable populations. Providers with higher proportions of high-risk, Black, low-income, or low-education patients show substantially larger increases in opioid prescriptions when experiencing lower wealth growth. These results suggest that providers are potentially less responsible in their opioid prescriptions for patients already most vulnerable to opioid-related harms.

Our findings have important implications for healthcare policy and the ongoing opioid crisis. They reveal a previously undocumented channel—providers' personal financial circumstances—through which economic conditions can affect opioid prescription patterns. The amplification of the effect in competitive healthcare markets suggests a potential tension between market pressures and public health interests that deserves careful consideration in policy design. The stronger effects among earlier medical school graduates point to the potential value of enhanced continuing medical education programs. Most critically, our results suggest that policies aimed at addressing the opioid crisis may need to pay special attention to vulnerable populations and the providers who serve them.

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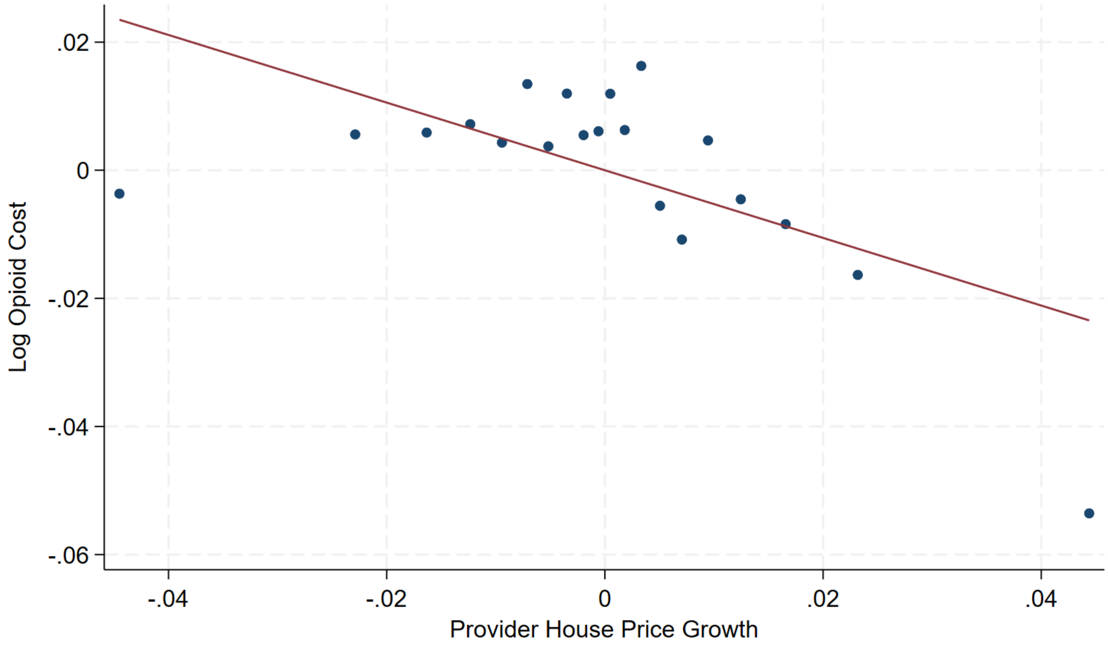
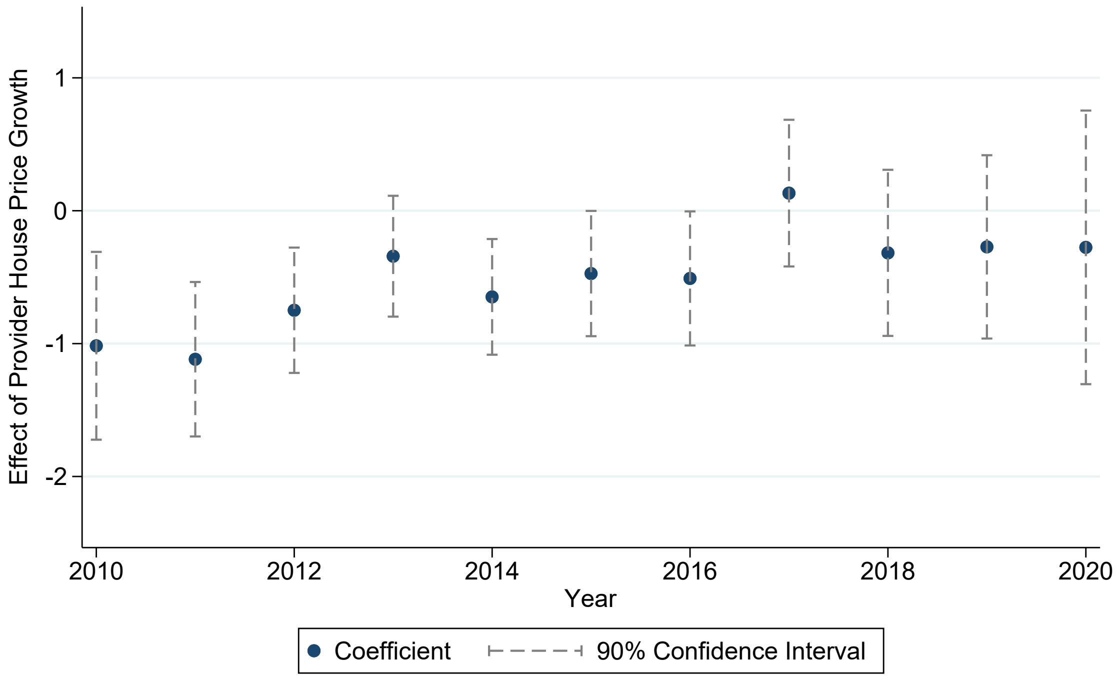
Figure 1: Opioid Prescriptions vs Provider House Price Growth



This figure presents a binscatter plot depicting the relation between healthcare providers' financial conditions and the amount of opioids they prescribe, after removing provider and office city–year fixed effects. The x-axis indicates *Provider Home Price Growth*, the annual growth rate of the provider's home price, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the last year. The y-axis indicates *Log Cost*, the natural logarithm of one plus the cost of opioids prescribed.

Figure 2: Effect of Provider House Price Growth on Opioid Prescriptions by Year

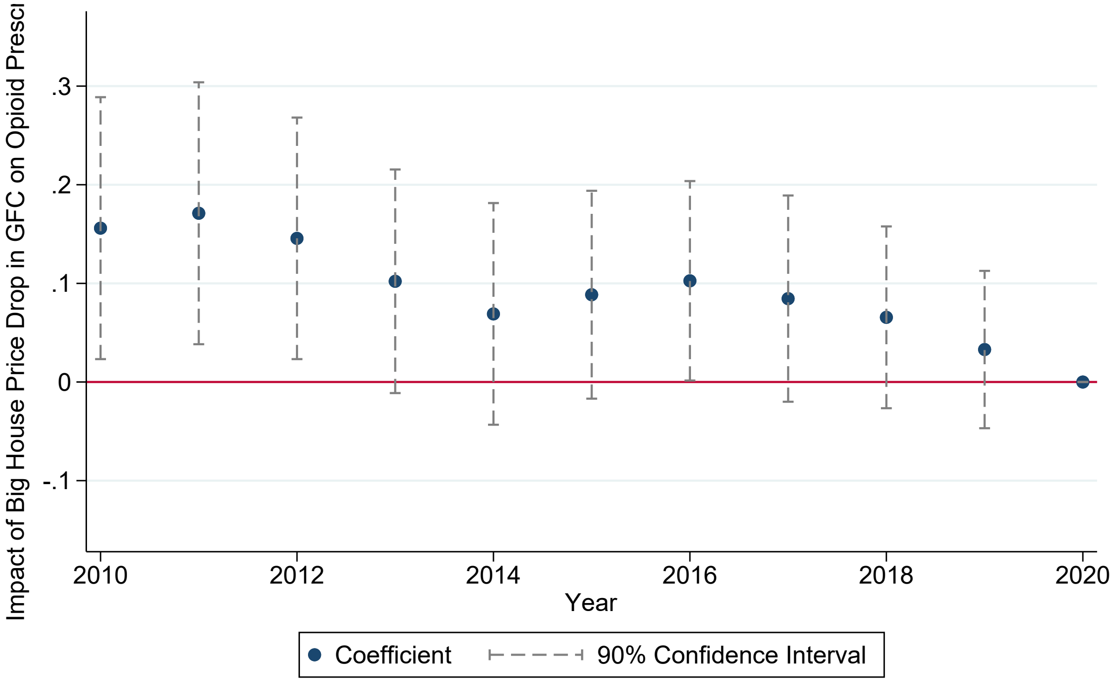


This Figure plots the year-by-year effect of healthcare providers' financial conditions on the amount of opioids they prescribe, estimated using Equation 2:

$$Log(Opioid\ Cost)_{p,t} = \sum_t \beta_t \times Home\ Price\ Growth_{z,t-1} \times 1(Year)_t + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}.$$

Log Opioid Cost is the natural logarithm of one plus the cost of opioids prescribed. *Provider Home Price Growth* is the annual growth rate of the provider's home price, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the last year. The dots represent the point estimates of β_t and the vertical lines represent 90 percent confidence intervals.

Figure 3: Effect of Large Price Drop During 2007-2009 on Opioid Prescriptions by Year



This Figure plots the effect of house price shock to health care providers during the Great Financial Crisis (GFC) of 2007-2009 on the amount of opioids they prescribe, estimated using Equation 3:

$$Log(Opioid\ Cost)_{p,t} = \sum_t \beta_t \times 1(Large\ Price\ Drop\ in\ GFC)_p \times 1(Year)_t + \alpha_p + \alpha_{l,t} + \epsilon_{p,t},$$

Log Opioid Cost is the natural logarithm of one plus the cost of opioids prescribed. *1(Large Price Drop in GFC)* indicates providers living in ZIP codes that experienced housing price growth change in the bottom half during 2007–2009.

Table 1: Summary Statistics

	Mean	SD	25 Pctl	Median	75 Pctl
Provider Home Price Growth	0.03	0.06	-0.00	0.03	0.06
Years aft Graduation	23.77	11.38	15	23	32
No Mortgage	0.27	0.45	0	0	1
Distance	11.94	10.21	4.22	8.92	16.98
Opioid Cost	9,185.56	18,864.55	414.90	2,119.55	8,878.73
Opioid Days Supply	5,188.21	8,091.22	520.00	2,084.00	6,274.00
Opioid Claims	218.68	318.56	31.00	98.00	267.27
Opioid Recipient	55.09	54.88	19.00	38.00	72.80
Opioid Cost/All Drug	0.06	0.13	0.00	0.01	0.04
Log Opioid Cost	7.24	2.68	6.03	7.66	9.09
Log Opioid Days Supply	7.13	2.47	6.26	7.64	8.74
Log Opioid Claims	4.39	1.72	3.47	4.60	5.59
Log Opioid Recipient #	3.48	1.29	3.00	3.66	4.30

This table presents summary statistics of variables used in our estimations. *Provider Home Price Growth* is the annual growth rate of the provider's home price, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the last year. *No Mortgage* is an indicator that equals one for providers without mortgages, and zero otherwise. *(Log) Opioid Cost/Days Supply/Claims* is (the natural logarithm of one plus) the cost of opioids prescribed/days supplied/claims. *Opioid Cost/All Drug* is the opioid cost divided by the cost of all drugs prescribed by the provider. *Log Opioid Recipient #*, which is the natural logarithm of one plus the number of patients receiving opioid prescriptions.

Table 2: Provider Home Price Growth Affects Opioid Prescription

(a) Provider & Office City-by-Year Fixed Effects

	Log Opioid Cost	Log Opioid Days Supply	Log Opioid Claims	Log Opioid Recipient #
	(1)	(2)	(3)	(4)
Provider Home Price Growth	-0.528***	-0.494***	-0.335***	-0.207***
	(-4.27)	(-4.22)	(-4.59)	(-3.24)
Provider FE	Y	Y	Y	Y
Office City $\times$ Year FE	Y	Y	Y	Y
Y Mean	7.253	7.137	4.396	3.512
Y SD	2.678	2.470	1.716	1.266
X Mean	0.027	0.027	0.027	0.047
X SD	0.057	0.057	0.057	0.043
N	619,813	619,813	619,813	409,556

(b) Provider & Office Zip-by-Year Fixed Effects

	Log Opioid Cost	Log Opioid Days Supply	Log Opioid Claims	Log Opioid Recipient #
	(1)	(2)	(3)	(4)
Provider Home Price Growth	-0.459***	-0.410***	-0.272***	-0.150**
	(-3.72)	(-3.53)	(-3.76)	(-2.33)
Provider FE	Y	Y	Y	Y
Office Zip $\times$ Year FE	Y	Y	Y	Y
Y Mean	7.261	7.144	4.400	3.517
Y SD	2.674	2.465	1.713	1.262
X Mean	0.027	0.027	0.027	0.047
X SD	0.057	0.057	0.057	0.043
N	611,885	611,885	611,885	403,280

This table examines the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 1. The dependent variables are the opioid prescription amounts: *Log Opioid Cost*; *Log Opioid Days Supply*; *Log Opioid Claims*; and *Log Opioid Recipient #*, which is the natural logarithm of one plus the number of patients receiving opioid prescriptions. *Provider Home Price Growth* is the annual growth rate of the provider's home price, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the last year. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Table 3: Provider Home Price Growth Affects Opioid Prescription: Robustness

	Opioid Cost/All Drug	Log Short-Acting Opioid Cost	Log Opioid Cost	
	(1)	(2)	(3)	(4)
Provider Home Price Growth	-0.023***	-0.424***	-0.522***	-0.462***
	(-4.08)	(-3.06)	(-3.06)	(-2.80)
Sample Restriction			Home Far to Office	
Provider FE	Y	Y	Y	Y
Office Zip $\times$ Year FE	Y	Y	Y	
Office $\times$ Year FE				Y
Y Mean	0.057	6.896	7.150	7.441
Y SD	0.130	2.732	2.689	2.503
X Mean	0.027	0.027	0.028	0.027
X SD	0.057	0.056	0.056	0.056
N	611,885	452,474	288,405	374,213

This table presents various robustness tests that examine the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 1. *Opioid Cost/All Drug* is the opioid cost divided by the cost of all drugs prescribed by the provider. *Log Short-Acting Opioid Cost* is the natural logarithm of one plus the cost of non-long-acting opioid prescription. *Log Opioid Cost* is the natural logarithm of one plus the cost of opioids prescribed. Column (3) uses a subsample of providers with distances between home and offices that are higher than the sample median. Column (4) includes granular fixed effects, with *Office* referring to the provider's office Placekey ID, the identifier for a physical place. t-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Table 4: Effect on Opioid Prescription is Stronger When Provider has No or Less Mortgage

	Log Cost			
	(1)	(2)	(3)	(4)
Provider Home Price Growth × No Mortgage	-1.345***	-1.320***		
	(-10.04)	(-9.72)		
Provider Home Price Growth × Low LTV			-0.703***	-0.725***
			(-3.77)	(-3.80)
Provider Home Price Growth	-0.108	-0.050	-0.747***	-0.668***
	(-0.83)	(-0.38)	(-4.32)	(-3.83)
No Mortgage	-0.044**	-0.046**		
	(-2.12)	(-2.20)		
Low LTV			0.010	0.010
			(0.53)	(0.49)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	7.253	7.261	7.179	7.190
Y SD	2.678	2.674	2.612	2.605
X Mean	0.027	0.027	0.031	0.031
X SD	0.057	0.057	0.057	0.057
N	619,697	611,770	333,840	324,360

This table examines the heterogeneous effect of healthcare providers' home equity on the effect of their financial condition on the amount of opioids they prescribe, estimated using Equation 4. *Log Opioid Cost* is the natural logarithm of one plus the cost of opioids prescribed. *No Mortgage* is an indicator that equals one for providers without mortgages, and zero otherwise. *Low LTV* is an indicator that equals one if the provider's loan-to-value ratio falls in the bottom quintile, and zero otherwise. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Table 5: Effect on Opioid Prescription is Stronger with Provider Competition

	Log Opioid Cost	
	(1)	(2)
Provider Home Price Growth × High Competition	-0.626**	-0.385
	(-2.08)	(-1.26)
Provider Home Price Growth	-0.364***	-0.367***
	(-2.65)	(-2.67)
Provider FE	Y	Y
Office City × Year FE	Y	
Office Zip × Year FE		Y
Y Mean	7.253	7.261
Y SD	2.678	2.674
X Mean	0.027	0.027
X SD	0.057	0.057
N	619,674	611,744

This table examines the heterogeneous effect of market competition on the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 4. *Log Opioid Cost* is the natural logarithm of one plus the cost of opioids prescribed. We construct a Herfindahl-Hirschman Index (HHI) at the cityâyear level, using the total Part D beneficiaries of the providers in our sample to measure their market shares. *High Competition* is an indicator that equals one if, within a year, a city's HHI falls in the bottom quintile, and zero otherwise. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Table 6: Effect on Opioid Prescription is Stronger for Older Provider

	Log Opioid Cost	
	(1)	(2)
Provider Home Price Growth × Graduated Earlier	-1.393***	-1.408***
	(-11.13)	(-11.10)
Provider Home Price Growth	0.109	0.162
	(0.91)	(1.36)
Provider FE	Y	Y
Office City × Year FE	Y	
Office Zip × Year FE		Y
Y Mean	7.494	7.503
Y SD	2.437	2.432
X Mean	0.027	0.027
X SD	0.056	0.055
N	499,493	491,339

This table examines the heterogeneous effect of age on the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 4. *Log Opioid Cost* is the natural logarithm of one plus the cost of opioids prescribed. *Graduatd Earlier* is an indicator that equals one if the provider's number of years since graduation falls in the bottom quintile, and zero otherwise. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Table 7: Effect on Opioid Prescription is Stronger for Nurse Practitioners

	Log Opioid Cost	
	(1)	(2)
Provider Home Price Growth × Nurse Practitioner	-2.018***	-1.653***
	(-7.13)	(-5.71)
Provider Home Price Growth	-0.357***	-0.307**
	(-2.80)	(-2.41)
Provider FE	Y	Y
Office City × Year FE	Y	
Office Zip × Year FE		Y
Y Mean	7.252	7.260
Y SD	2.679	2.675
X Mean	0.027	0.027
X SD	0.057	0.057
N	597,343	589,763

This table examines the heterogeneous effect of age on the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 4. *Log Opioid Cost* is the natural logarithm of one plus the cost of opioids prescribed. *Nurse Practitioner* is an indicator that equals one if the provider is a nurse practitioner, and zero otherwise. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.

Table 8: Effect on Opioid Prescription is Stronger for Vulnerable Patients

	Log Opioid Cost			
	(1)	(2)	(3)	(4)
Provider Home Price Growth × More High-Risk Patients	-0.320**			
	(-2.24)			
Provider Home Price Growth × More Black Patients		-0.526***		
		(-2.56)		
Provider Home Price Growth × ZIP Low Income			-0.826***	
			(-4.41)	
Provider Home Price Growth × ZIP Low Education				-0.330*
				(-1.70)
Provider Home Price Growth	-0.187	0.065	-0.312**	-0.427***
	(-1.22)	(0.40)	(-2.40)	(-3.29)
More High-Risk Patients	0.087***			
	(5.69)			
More Black Patients		-0.030		
		(-1.16)		
ZIP Low Income			-0.049	
			(-1.24)	
ZIP Low Education				0.012
				(0.26)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y	Y	Y	Y
Y Mean	7.112	7.514	7.258	7.257
Y SD	2.804	2.494	2.677	2.677
X Mean	0.047	0.045	0.027	0.027
X SD	0.043	0.043	0.057	0.057
N	479,737	243,740	614,905	615,888

This table examines the heterogeneous effect of age on the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 4. *More High-Risk Patients* is an indicator that equals one if the average Hierarchical Condition Category (HCC) risk score of a provider's patients is above the sample median, and zero otherwise. *More Black Patients* is an indicator that equals one if the percentage of black patients for a provider falls in the top quintile, and zero otherwise. *ZIP Low Income* is an indicator that equals one if the median income of the provider's office ZIP falls in the bottom quintile, and zero otherwise. *ZIP Low Education* is an indicator that equals one if the percentage of residents with a bachelor degree and above of the provider's office ZIP falls in the bottom quintile, and zero otherwise. *t*-statistics, reported in parentheses, are based on standard errors that are clustered at the provider level. *, **, and *** denote statistical significance at 10%, 5%, and 1% level.