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HOW DO FINANCIAL CONDITIONS AFFECT PROFESSIONAL CONDUCT? EVIDENCE FROM OPIOID PRESCRIPTIONS

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ABSTRACT

We examine how healthcare providers' opioid prescriptions are affected by changes in their home values, which proxy for shocks to their wealth. We find that providers increase opioid prescriptions when experiencing adverse financial conditions. Results are robust to including provider office–year fixed effects and using the subsample of providers who live far away from their offices, thereby largely ruling out a patient–demand explanation. Providers living in ZIP codes with price changes in the bottom half in 2007–2009 increased their opioid prescriptions in 2010–2012 by approximately 16% more than others. The effect is stronger among providers facing more provider competition and those serving vulnerable populations. Providers experiencing adverse financial conditions also receive more opioid-related payments from pharmaceutical companies. We also extend our analysis to ADHD medications, demonstrating a similar pattern of increased prescriptions under negative financial shocks, suggesting broader implications for other medical decisions. Our findings offer novel insights into professional conduct under personal financial pressure, with implications extending beyond healthcare.

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1 Introduction

To what extent can personal financial pressure compromise professional conduct? The answer has broad implications for trust in professional judgment, the design of incentive structures, and the protection of vulnerable customers. This question takes on profound significance in healthcare, where providers pledge to "do no harm" and where their decisions directly impact patient health outcomes. How healthcare providers' personal financial circumstances affect their clinical choices remains unexplored, despite the critical implications for healthcare policy and patient protection. Although our study focuses on healthcare, the mechanisms through which financial pressure influences professional conduct are likely transferable to a wide array of fields where conflicts of interest between personal financial gain and client welfare may emerge.

This study examines whether healthcare providers' financial health affects their prescribing behavior. We focus on opioid prescriptions, as the opioid crisis represents a significant public health challenge with substantial societal impacts, and experts worry that recent policy changes may exacerbate the crisis.[1] We also extend our analysis to Attention-Deficit/Hyperactivity Disorder (ADHD) medications, another class of drugs with significant potential for overprescription. Both categories have been subject to anecdotal reports of inappropriate prescribing. The insights revealed through our analysis are likely applicable to other medications with significant potential for misuse, as well as other medical practices beyond prescriptions.

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. In our baseline specification, we include office city or ZIP by year fixed effects, controlling for the average house price trend in the same city or ZIP. Importantly, the result is robust when estimated relative to other providers within the same office in the same year using office by year fixed effects. The result is also robust when restricting

[1] See, https://www.nytimes.com/2025/08/28/opinion/opioids-progress-trump-policy-law.html

to the sample of providers who live far away from their offices. Thus, it is unlikely that the patients' demand drives our result.

This result is consistent with the idea that, faced with a negative wealth shock, providers prescribe more opioids, possibly to ensure repeated patient visits. This result also implies that financial pressures might influence medical decision-making across various domains, potentially at the expense of patient health. Our findings have important implications for healthcare policy, medical ethics training, the structure of provider compensation, and strategies to prevent similar crises involving other addictions induced by prescription medication. The implications can also extend beyond healthcare to other professions with conflicts of interest, suggesting that personal financial shocks and broader economic downturns can compromise professional conduct.

How do providers benefit financially from increased prescribing and patient volume? First, volume-based compensation is the most common type of base pay for over 84% of primary care doctors and over 93% of specialists; when volume-based incentives were included in compensation plans, they accounted for more than two-thirds of providers' compensation (Reid et al., 2022). 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 patient visits. By prescribing opioids, providers may increase patient volume through attracting patients who seek opioids and serving opioid-addicted repeat visitors. Indeed, our analysis suggests that, when providers prescribe more opioids, they deliver more healthcare services and submit more charges for these services to Medicare in the following year.

There is another channel through which providers can benefit financially through opioid prescriptions. According to Schneider et al. (2022), 77% of healthcare facilities conduct patient satisfaction surveys and 22% incorporate these results into provider compensation decisions. This practice may incentivize the prescription of medications that

offer immediate relief or fulfill patient expectations, such as opioids. Patients experiencing pain are more likely to report high satisfaction when providers prescribe opioids given their superior analgesic properties, while those seeking opioids due to existing addiction or illicit trading are satisfied simply by receiving their desired medication. Supporting this hypothesis, Sites et al. (2018) find that among musculoskeletal pain patients, those who received more opioid prescriptions were more likely to report high satisfaction scores. Furthermore, Carrico et al. (2018) find that 36% of providers subject to satisfaction-based financial incentives acknowledge that these surveys affect their opioid prescribing practices. Collectively, all this evidence suggests that providers may enhance patient satisfaction scores—and thus their compensation—by prescribing opioids.

We use house price growth in providers' residential ZIP codes to proxy for shocks to their financial conditions. Why would changes in house prices matter to professional behavior? Housing wealth affects individuals through multiple channels beyond its direct impact on net worth. First, housing appreciation increases borrowing capacity through home equity lines of credit (HELOC), and cash-out refinancing options. Second, higher home values enhance homeowners' mobility by enabling purchases of more expensive properties. Third, house price gains create additional wealth available for consumption or bequests upon property sale. Empirical research demonstrates that housing wealth shocks influence labor market choices (Bernstein, 2021), risk-taking behavior (Pool et al., 2019), consumption patterns (Campbell and Cocco, 2007; Aladangady, 2017; Berger et al., 2017), and local retail markups (Stroebel and Vavra, 2019). From a research design perspective, housing price changes offer two methodological advantages. They vary at granular geographic levels and over time, allowing us to isolate the effects of providers' personal financial conditions from other confounding factors. Additionally, the 2007-2009 financial crisis, during which healthcare providers experienced heterogeneous housing wealth losses, offers exogenous variation to examine how financial distress affects professional conduct.

To test how providers' financial conditions affect their opioid prescriptions, we use detailed provider-year-level Medicare drug coverage (also known as Part D) prescription data, matched with house price growth rates at providers' residential ZIP codes. Our sample includes 92,937 providers in all 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 percentage points) leads providers to prescribe 3% more opioids. Importantly, 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. This result suggests that providers are not simply working more, but rather adjusting their clinical judgment in response to personal wealth shocks. This adjustment in clinical judgment is a key behavioral channel that has implications for various forms of medical decision-making beyond just prescription choices.

Second, we find that slower house price growth is associated with increased service delivery and higher charges submitted to Medicare in the following year. This pattern is consistent with our hypothesis that when providers experience adverse house price shocks, they seek to increase their compensation through higher service volume, whether by increasing their overall practice intensity or by using opioid prescriptions as a tool to attract more patient visits.

Third, we also find that providers experiencing adverse house price growth are more likely to receive payments related to opioids from pharmaceutical companies. When providers experience a one-standard-deviation decrease in house price growth, their probability of receiving opioid-related payments increases by 5% relative to the baseline. These payments, which must be reported under the Sunshine Act, typically take the form of marketing activities such as lunch meetings with sales representatives, as well as consulting

and speaking fees. This result provides additional evidence that providers under financial pressure may be more receptive to pharmaceutical companies' marketing efforts, complementing our main finding on providers' opioid-prescribing decisions.

Fourth, the Great Financial Crisis (GFC) of 2007-2009 provides an opportunity to investigate how large housing wealth shocks influence prescribing behavior. We find that providers residing in areas experiencing larger-than-median housing price declines during the 2007-2009 financial crisis period increased their opioid prescriptions by approximately 16% more in 2010-2012 compared to providers residing in other areas. This difference diminished after 2012, possibly due to the housing market recovery. In addition, we find that when providers experience a bottom-decile house price growth rate (corresponding to a decline of at least 4%) outside the GFC, their opioid prescriptions increase by 3% in the following year.

Fifth, we uncover heterogeneity in providers' opioid prescription response to house price shocks along several dimensions. 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.

In addition, the effects are also particularly pronounced among nurse practitioners. Due to their lower labor 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' prescription responses to house price changes are five times as large.

Moreover, we find that the relationship between providers' financial stress and opioid prescriptions is stronger among providers serving more vulnerable populations. Specifically, providers 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 addiction.

Another heterogeneity is in relation to the regulation of opioid prescription. To address opioid overprescription, states implemented regulatory measures including pill mill laws, prescription drug monitoring programs (PDMPs), and prescribing limits (Finkelstein et al., 2025). Using a stacked difference-in-differences approach, we find that the influence of physicians' house price growth on opioid prescribing is concentrated in the pre-policy period and becomes statistically insignificant after policy adoption, suggesting that state regulations reduced the impact of financial pressures on prescribing decisions. These findings imply that policy interventions can potentially mitigate inappropriate healthcare decisions driven by providers' financial incentives in other clinical contexts.

Finally, we extend our analyses to ADHD medications, which are also identified as a class of drugs with significant potential for misuse and have been subject to anecdotal reports of inappropriate prescribing, similar to opioids. Focusing on the sample period from 2013 onwards, a period when ADHD drugs gained increased attention among potential recipients, we find a similar pattern to that observed with opioids: providers increase their prescription of ADHD drugs when they experience a relatively lower house price growth. This finding suggests that the influence of providers' financial health on prescribing behavior may extend beyond opioids to other medications with overprescription potential.

Although the implications of our paper should extend beyond the Medicare provider and patient population, our focus on Medicare beneficiaries, who are generally older, is particularly important given the growing opioid crisis among older adults and their heightened physiological vulnerability. Medicare beneficiaries have among the highest and fastest-growing rates of diagnosed opioid use disorder, affecting more than 6 of every 1,000 beneficiaries (Centers for Medicare & Medicaid Services, 2017). Those aged 60 and over have a 30-day opioid use rate of 7.9%, compared to 4.7% for those aged 20-39 (Frenk et al., 2015), and adults aged 65 and older comprise 25.4% of long-term opioid users (Mojtabai, 2017). This vulnerability is compounded by age-related changes:

as people age, medications affect them more strongly and are slower to leave their systems, making opioid side effects particularly severe (Tilly et al., 2017). Opioid overdose deaths among those 55 and older increased tenfold from 1999 to 2019, rising from 0.9 to 10.7 per 100,000 population (Mason et al., 2022). Our use of the Medicare data therefore addresses a critical public health concern.

Our findings have several important implications for healthcare policy and the ongoing opioid crisis. First, they offer novel insight that providers' personal financial circumstances can influence medical decision-making, potentially at the expense of patient health. While existing research has primarily focused on patient-side economic factors or broad regulatory changes, our results suggest that healthcare providers' financial stress can meaningfully influence their prescription decisions. Our findings indicate that moving providers away from volume-based compensation can reduce over-perscription of opioids and other addictive medications. More broadly, compensation reform can mitigate incentives for unnecessary medical services to prevent wasteful medical spending and promote patient health.

Moreover, the effects being stronger in more competitive healthcare markets suggest that market pressures may sometimes work against public health interests. While competition is generally thought to be beneficial, our findings indicate that it might create incentives for healthcare providers under financial stress to prescribe more addictive medications to satisfy patient demand rather than prioritize optimal care. This tension between market competition and provider behavior deserves careful consideration in healthcare policy design. Moreover, we find that nurse practitioners' prescriptions respond to financial shocks significantly more than those of physicians. This creates additional concerns in the recent healthcare environment, relying more and more on nurse practitioners. Our results therefore complement those in Currie et al. (2023), who find that as U.S. state law changes granted nurse practitioners the authority to prescribe controlled substances, the increased provider competition led to more opioid prescriptions on average.

Finally, our findings suggest that financial pressure may disproportionately compromise care quality for patients from low-income and low-education communities. These results are particularly concerning given that these communities face heightened susceptibility to opioid addiction and its associated harms.[2] Our findings indicate that policies aimed at addressing healthcare providers' conduct should prioritize oversight and support for providers serving vulnerable populations.

The implications can extend beyond the healthcare setting to other professions with potential conflicts of interest. Our findings reveal that economic stress can compromise professional decision-making and are applicable in fields like finance, law, consulting, education, and many others. Employers and regulators should monitor professional conduct more closely during negative local/sectoral shocks, as well as during economic downturns. When financial stress affects many professionals simultaneously, the risk of compromised decision-making may increase across entire sectors or regions.

1.1 Contribution to the Literature

Our paper makes several important contributions to the literature. First, we contribute to the literature on personal financial conditions and professional conduct by showing that worsening financial conditions can cause professionals to potentially compromise client welfare. Two papers are particularly relevant. Dimmock et al. (2021) find a negative relationship between financial advisors' housing returns and misconduct. Maturana and Nickerson (2020) find that students' performance declines after teachers file for bankruptcy, most likely due to decreased effort from the teachers.

Our contribution extends beyond their work in two important ways. Due to data limitations, Dimmock et al. (2021) cannot determine whether increased misconduct simply reflects advisors working more intensively or becoming more prone to misconduct. We

[2]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).

demonstrate that providers specifically increased their opioid prescriptions as a proportion of their total drug prescriptions following adverse housing price movements. Our findings suggest a deliberate shift in prescribing patterns rather than merely increased activity levels or decreased effort as in Maturana and Nickerson (2020). This potentially concerning adjustment of professional judgment in response to financial stress is a crucial insight that could be applicable to fields beyond medicine, such as finance (e.g., advising on higher-commission products), law (e.g., prolonging litigation), or consulting (e.g., recommending unnecessary projects), where professionals may similarly adjust their conduct to secure client retention or increase revenue, potentially compromising client interests.

We also differentiate our paper by exploring whether the effect of personal wealth shocks can have implications among healthcare providers who pledged to do no harm. Understanding their opioid prescription behavior can shed light on the opioid crisis and healthcare provider behavior. A contemporaneous paper by Wang (2025) is also highly relevant. He finds that physicians' lower housing returns are related to more C-section surgeries, providing complementary evidence.

Second, we contribute to the literature examining the relationship between healthcare providers' financial incentives and their prescribing behavior and other clinical choices. A number of studies document a positive correlation between payments received by providers from pharmaceutical companies and their opioid prescriptions.[3] Relatedly, Currie et al. (2023) find that more competition among healthcare providers leads to more opioid prescriptions, which can also be explained by providers facing financial incentives to secure a larger patient base. More generally, several studies examine how institutional financial incentives (e.g. Medicare/Medicaid reimbursement rates) affect providers' service supply.[4] We contribute by revealing that providers' personal financial conditions—rather than

[3]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).

[4]See, Hackmann et al. (2024), Alexander and Schnell (2024), Einav et al. (2018), Clemens and Gottlieb (2014), and Batty and Ippolito (2017).

payments or market-level competition—can affect their prescribing decisions for medications with misuse potential.[5] The implications of our findings differ from papers on financial incentives: during economic downturns or local/sectoral shocks affecting healthcare providers and other professionals, we may observe concerning shifts in professional conduct that compromise service quality or client welfare.

A growing literature studies the drivers and economic effects of the opioid crisis. Maclean et al. (2020) provide a review of economic studies on demand and supply-side drivers, estimates of economic costs, policies, as well as healthcare, crime, and economic outcomes. In the finance literature, Ouimet et al. (2023) find that opioid prescriptions reduce employment and establishment growth.[6] Several papers study policy interventions aimed at curbing inappropriate opioid prescribing.[7] We contribute to this literature by revealing that opioid prescriptions are affected by providers' financial health.

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.[8] Between 2001 and 2016, opioid-related deaths increased by 292%, from 33.3 to 130.7 deaths per million population (Gomes et al., 2018).

[5] More broadly, our paper is related to several papers examining the relationship between hospital financial conditions and clinical choices or prices (Dranove et al., 2017; Adelino et al., 2022; Aghamolla et al., 2024; Gao et al., 2024).

[6] Cornaggia et al. (2022) show that opioid abuse increases municipalities' borrowing costs and reduces their bond issuance. Li and Ye (2022) find that local opioid epidemics transmit negative financing shocks to other regions through the banking sector. Cornaggia et al. (2023) find that opioid abuse has negative effect on local innovation activities.

[7] See, Kim (2021); Finkelstein et al. (2025); Stone et al. (2020).

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

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 in 2017.[9] The COVID-19 pandemic subsequently 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.[10]

The role of prescription opioids in the opioid crisis is evidenced 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.[11] Other major settlements include a $26 billion agreement with Johnson & Johnson and three major pharmaceutical distributors—AmerisourceBergen, Cardinal Health, and McKesson.[12] 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.[13] The funds from these settlements are now being distributed to states and local governments to support opioid treatment, prevention, and recovery programs.[14]

To curb the overprescription of opioids, states established Prescription Drug Monitoring

[9] See, https://www.hrsa.gov/opioids.

[10] See, https://www.osc.ny.gov/reports/continuing-crisis-drug-overdose-deaths-new-york.

[11] See, https://www.americanbar.org/news/abanews/aba-news-archives/2019/09/opioid-lawsuits-generate-payouts-controversy/.

[12] See, https://www.naag.org/issues/opioids/.

[13] See, https://www.bmj.com/content/379/bmj.o2688.

[14] See, https://ag.ny.gov/nys-opioid-settlement.

Programs (PDMPs). These programs created databases on patients' current or past use of controlled substances. Access to this database before prescribing opioids was voluntary for medical providers at first. However, this voluntary access led to only a small fraction of providers accessing the information. In response, 16 states shifted to a must-access system between 2012 and 2017. This mandated review of controlled substance prescription history helps providers identify high-risk patterns (such as multiple prescriptions from different doctors) and increases the risk of doctors facing lawsuits, thereby discouraging inappropriate prescribing. 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). Even so, drug overdose deaths, a 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 opioid prescription patterns.

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).[15] CMS has developed the NPPES to assign these unique identifiers. Once assigned, an NPI remains the same, even if the provider has a change of name, address, or other information. In September 2007, CMS began disclosing NPPES healthcare provider data under the Freedom of Information Act (FOIA) to the public.[16] The data are updated monthly and cover both the active and deactivated providers. Importantly, healthcare providers with active NPIs cannot opt out or request 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 obtain additional information on the provider's medical school and graduation year.[17] We then geolocate providers' practice location addresses to obtain the latitudes and longitudes, and the identifier for the practice address (Placekey).[18]

3.2 Property Information

We obtain a national database of property tax and deed records from CoreLogic, a premier real estate transaction data provider. The deed records cover the near universe of housing transactions starting from the 1990s,[19] with more than 850 million historical real estate

[15] 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.

[16] 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`.

[17] The data are 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.

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

[19] 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."

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, as well as property characteristics. Moreover, CoreLogic has processed the data to generate valuable information, such as parsing names into first/middle/last names and geolocating the addresses to obtain the latitude and longitude of the property.

CoreLogic data have 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 require providers to 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 a provider to own a certain property in a year if it was purchased before that year and not sold during that year. When the purchase or sale date is missing, we check whether the provider pays property tax for the property in a year to determine home ownership.

We obtain the ZIP code level Zillow Home Value Index (ZHVI) at the monthly frequency from Zillow. The data are available to us from January 2001 until 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 obtain the provider's prescription information from Medicare Part D (Prescription Drug Coverage). The data cover information on prescription drugs to Medicare beneficiaries enrolled in Part D, 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 obtain individual healthcare providers' prescription behavior. These data are aggregated at the provider-year level and are available since 2013. Since our version of CoreLogic data is only available until February 2021, we end our sample period in 2020.

The Part D data contain overall drug and opioid drug utilization (claims and days' supply), drug costs, and beneficiary counts aggregated by provider and year. In addition, CMS provides data on beneficiary demographic and health characteristics, which include age, sex, race, and health risk scores.

To protect the privacy of Medicare beneficiaries, CMS suppresses the drug prescription quantity (beneficiary count) 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 are dropped in regressions. We then define a dummy variable (*Opioid Dummy*) indicating whether the provider prescribes opioid drugs, and set it to one if the opioid drug prescription quantity is suppressed or larger than 0. Analysis using *Opioid Dummy* includes all the observations.[20]

We further obtain the 2010-2012 Part D data from ProPublica, a nonprofit investigative journalism organization, which obtained Medicare Part D data from the CMS under the FOIA.[21] The data are at the provider-year-drug level, and we use the Medicare Part D Opioid drug list provided by CMS to aggregate the data to obtain 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.[22]

[20] CMS suggests 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.

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

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

3.4 Sample

We have the following data filtering steps for sample construction. We begin with the combined Medicare Part D data. The first filtering step focuses on medical specialties. Specifically, we exclude medical specialties that have fewer than 1,000 providers in the data. Additionally, we eliminate providers who work in hospitals because these providers are less likely to attract repeat visits from patients through opioid prescriptions. Specifically, we exclude specialties related to hospital care.[23] Additionally, we also drop providers who work within hospitals. Specifically, we drop providers whose practice location addresses include the keywords hospital, emergency, or urgent, and also exclude providers whose addresses can be matched to hospital addresses in the Healthcare Cost Report Information System (HCRIS) data, provided by CMS. We also exclude providers who are students participating in an Organized Health Care Education/Training Program. Their compensation is unlikely to be affected by patient volume, so they have less financial incentive to prescribe opioids. We then further exclude providers of the following specialties: hospice, oncology, urology, obstetrics and gynecology, optometrist, dermatology, dentist, ophthalmology, advanced practice midwife, and radiology. Providers in these fields typically prescribe opioids primarily for procedural pain management rather than for routine visits, the latter of which are more likely to encourage patient return and potential income growth. The last step retains the practice location ZIP code–medical specialty pairs with multiple providers during the sample period. 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 obtain providers' property information, and then merge with Zillow data to obtain information on the house price growth rate at the ZIP code of the property. In this sample, 77% of the providers have only one property, 17% have two, 5% have three, and 1% have more than three. We aggregate

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

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.[24] Our final sample includes 92,937 providers practicing in 8,730 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 rate (in log differences). There are significant variations in housing price growth rates, with a standard deviation of 6%. The average distance between providers' homes 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, totaling 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 Opioid Prescription Brings More Patient Business

Our central hypothesis posits that providers' financial health influences their professional behavior, specifically opioid prescribing practices. This relationship relies on the assumption that if providers prescribe more, it can generate higher business volume and income for them. The mechanism underlying this assumption operates through two channels. First, patients receiving opioid prescriptions may develop dependencies, thereby increasing their likelihood of returning to the same provider for continued care. Second, patients who are already dependent on opioids or seeking to obtain them for resale may actively seek out or return to providers who prescribe opioids without any clinical basis. In both

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

cases, providers who accommodate these demands can generate more patient visits and, thus, higher income.

To test this hypothesis, we use data from Medicare Part B, which covers 80% of physician visit costs and represents 49% of the $1.01 trillion in Medicare spending for 2023.[25] This dataset provides provider-year level information on service delivery volumes and submitted charges, among other key metrics.

Table 2 examines how these business outcomes are related to providers' previous-year opioid prescriptions. Our dependent variables are the log amount of services delivered (Columns 1-2) and the log amount of charges submitted (Columns 3-4).[26] The independent variable is providers' opioid prescriptions from the previous year, measured in the natural log of dollar costs.

We control for provider fixed effects in all specifications. In addition, we incorporate progressively more restrictive location–year controls: office city–year fixed effects in Columns (1) and (3) and office ZIP–year fixed effects in (2) and (4).

The estimated coefficients on lagged opioid prescriptions are consistently positive and statistically significant across all specifications. This result indicates that providers who prescribed more opioids in the previous year subsequently delivered more services and submitted higher charges in the current year. The magnitude of our estimates suggests that a 1% increase in providers' lagged opioid prescriptions corresponds to approximately a 0.04% increase in both services delivered and charges submitted.

These findings are consistent with multiple potential mechanisms. First, patients receiving opioid prescriptions may develop dependencies that increase their likelihood of returning to the same provider for continued opioid prescriptions. Second, patients who are already dependent on opioids or seeking to obtain them for illicit purposes may engage in "doctor shopping," actively seeking providers known to prescribe opioids more readily.

[25] See, `https://www.kff.org/interactive/the-facts-about-medicare-spending/`.

[26] To eliminate the effect of number of working days on these outcome variables, we standardize raw services and charges by dividing by actual days worked and multiplying by 260.

Providers who accommodate these requests may cultivate patient loyalty that drives repeat visits.

Alternatively, the results in this section can arise from unobserved factors simultaneously driving both increased opioid prescription and higher service provision in subsequent periods. Our findings here provide suggestive support for the underlying assumption of our main hypothesis that financial incentives may influence providers' professional behavior. We test this hypothesis in the following section.

5 Provider Financial Health Affects Opioid Prescription

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: $Log(HPI_{z,t-1}) - Log(HPI_{z,t-2})$.

In Table 3, we start with the dependent variable being *Log Opioid Cost*, the natural logarithm of one plus the cost of opioids prescribed in Columns (1)-(5). All columns include provider fixed effects. In addition, Column (1) also includes providers' office city–year fixed effects. Column (2) also includes providers' office ZIP–year fixed effects. We refer to Column (1) as our benchmark specification. The sample period is between 2010 and 2020, as explained in the Data section. We correct standard errors for clustering of observations at the provider level.

The estimated coefficients on *Provider House Price Growth* are negative and statistically

different from zero in all columns. The magnitudes are also economically meaningful. According to Column (1), when a provider experiences a one-standard-deviation slower house price growth, approximately 6% lower, she prescribes 3% ($=0.06\times0.5$) more opioids.

A potential concern with our analysis is that providers' home price growth might be correlated with their patients' financial health if providers and patients tend to live in proximity to one another. 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 (3) repeats our benchmark specification using a subsample of providers whose home-to-office distance exceeds the median. In this subsample, the home-to-office distance has a mean of 20 kilometers and a median of 17 kilometers. The estimated coefficient on *Provider Home Price Growth* is similar to 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. Column (4) includes providers' office ZIP–specialty–year fixed effects. Results are similar.

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, thereby essentially controlling 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 to be driven by endogenous patient demand for opioids.

Figure 1 presents two binned scatter plots depicting the relationship between *Log Opioid Cost* and *Provider Home Price Growth*. Panel (a) uses the raw variables, while Panel (b)

first removes provider and office ZIP–year fixed effects. Both plots reveal a clear negative relationship between these variables, corroborating our regression findings.

The frequent dosing requirements and intense peak effects associated with short-acting opioids create a higher propensity for dependence and misuse compared to their long-acting counterparts. Long-acting opioid drugs, while still carrying addiction risks, generally pose a lower threat of patient addiction compared to their short-acting counterparts. [27] If providers' low home price growth only increases their prescription of long-acting opioid drugs, the negative consequences are less severe. In Column (6), 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, which pose substantial risks for patient addiction.

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 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. This finding reinforces the idea that financial stress can induce a general propensity towards providing expedient treatment solutions, and not just over-prescribing addictive medications. We investigate whether this relationship is particularly pronounced for opioids.

In Column (7), we examine this by using the ratio of providers' opioid prescription costs to their total prescription costs as our dependent variable. The coefficient on *Provider Home Price Growth* remains negative and statistically significant, suggesting a disproportionately larger effect for opioid prescriptions. The economic magnitude is meaningful: a one-standard-deviation decrease in *Provider Home Price Growth* corresponds to a 2.7% increase

[27] For the full list of long-acting opioids, see: `www.fda.gov/drugs/information-drug-class/list-extended-release-and-long-acting-opioid-products-required-have-opioid-rems`.

relative to the average ratio of opioid costs to total drug costs.

In Table A1, we estimate equation 1 using various dependent variables, all measured at the provider–year level. The first dependent variable, *Log Opioid Days Supply*, is the natural logarithm of one plus total days of opioid supply. The second, *Log Opioid Claims*, is the natural logarithm of one plus the number of opioid prescriptions. Our third dependent variable, *Log Opioid Recipient #*, is the natural logarithm of one plus the number of patients receiving opioid prescriptions. The fourth dependent variable, *1(Opioid>0)* is an indicator that equals one if the provider prescribes any opioid in that year.[28] All specifications include provider and providers' office city–year fixed effects (as in Column 1 of Table 3). We find that the estimated coefficients on *Provider House Price Growth* are negative and statistically different from zero in all three columns. In other words, these alternative measures of opioid prescriptions all increase with lower house price growth for providers.

6 Effect of Provider Home Price Growth on Service Volume and Charges

Having established that slower home price growth increases opioid prescribing, we now test the complementary prediction that such changes should also increase providers' overall business activity. If providers respond to financial pressure by increasing opioid prescriptions to cultivate patient loyalty and boost income, we should observe that declining home prices or slower house price growth rates correlate with higher service volumes and charges submitted.

Table 4 examines this relationship using the same Medicare Part B data used in Table 2. Our dependent variables are the log amounts of services delivered (Columns 1-2) and

[28]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.

charges submitted (Columns 3-4). The key independent variable is *Provider Home Price Growth*, measured as the lagged home price growth in providers' residential ZIP codes. We maintain the same control structure: provider fixed effects throughout, with location controls progressing from office city–year to office ZIP–year fixed effects.

The results support our prediction. The estimated coefficients on *Provider Home Price Growth* are negative and statistically significant in all four specifications. Based on our estimates, a one-standard-deviation decrease in home price growth (4%) corresponds to a 0.4% increase in services delivered and a 0.3% increase in charges submitted. These effects complement our earlier findings on opioid prescribing, providing evidence that deteriorating financial health induces healthcare providers to alter their professional behavior in ways that boost business performance. Given that higher service volumes and charges typically translate to increased physician compensation, these results suggest that providers actively seek to offset negative wealth shocks by boosting their income.

7 Provider Financial Health Affects Opioid Payments from Pharmaceutical to Provider

Our findings indicate that providers increase their opioid prescriptions when experiencing adverse house price growth in their residential areas. This relationship raises questions about whether declining house prices also influence providers' interactions with pharmaceutical companies, particularly regarding opioid-related payments. These payments, which must be reported under the Sunshine Act, often take the form of marketing activities such as lunch meetings with sales representatives, consulting, and speaking fees. We hypothesize that providers facing financial pressure may be more receptive to pharmaceutical representatives' outreach efforts, making them more likely to attend informational meetings about opioid medications and receive associated payments.

In Table 5, we estimate Equation 1 by replacing the dependent variable with an indi-

cator for the provider receiving opioid-related payments in Columns (1) and (2) and the natural logarithm of one plus the dollar amount of the payments in (3) and (4). We control for provider fixed effects in all columns and add provider office city–year fixed effects in Columns (1) and (3) and provider office ZIP–year fixed effects in (2) and (4).

The coefficients on *Provider Home Price Growth* are negative and statistically significant across all specifications. Our estimates in Column (1) show that a one-standard-deviation decrease in house price growth increases a provider's probability of receiving opioid-related payments by 0.4 percentage points (0.096×0.043), representing a 3.3% increase relative to the baseline probability. Similarly, Column (3) indicates that such a decline in house price growth leads to a 1% increase in the amount of opioid-related payments that providers receive (0.251×0.043). While these magnitudes are modest, they provide supporting evidence for our main finding that providers' financial circumstances influence their opioid-prescribing behavior.

8 Effect of Home Price Declines on Opioid Prescriptions

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 of 2007 to the end of 2009. To exploit the historical house price shock during the Crisis, we estimate the following specification.

$$Log(Opioid\ Cost)_{p,t} = \sum_{t} \beta_t \times 1(Large\ Price\ Drop\ in\ GFC)_p \times 1(Year)_t + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \tag{2}$$

1(Large Price Drop in GFC) indicates providers living in ZIP codes that experienced housing price index changes 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 2 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.

In Table 6, Columns (1)-(2), we test whether any large negative home price growth between 2009 and 2019 influences opioid prescriptions in the following year. The dependent variable remains the natural log of prescribed opioid costs. Our key independent variable is an indicator for whether the previous year's house price growth in the provider's residential ZIP code fell within the bottom decile of our sample. This bottom decile experiences a maximum price change of -4% and a mean of -8%. Again, we control for provider fixed effects and office city–year or ZIP–year.

The estimated coefficients on the bottom decile indicator are positive and statistically significant. The magnitude indicates that, outside of crisis periods, providers experiencing bottom-decile home price changes prescribe approximately 3% more opioids.

In Columns (3)-(4), we employ a spline specification to separately estimate the effects of positive and negative price changes. Specifically, we replace the *Provider Home Price Growth* measure in Table 3 with two independent variables. The first one, *Provider Home Price Growth (<0)*, equals the raw home price growth measure when negative and zero otherwise. The second one, *Provider Home Price Growth (≥0)* equals the raw home price growth measure when non-negative and zero otherwise.

The estimated coefficients on both independent variables are all negative and mostly

statistically significant, confirming that lower house price changes are associated with more opioid prescriptions. The results suggest that our results are driven by when providers experience both actual housing wealth losses and merely slower gains. Importantly, the absolute magnitude of the coefficients is larger for *Provider Home Price Growth (<0)*, indicating that the relationship is more pronounced when providers experience actual wealth losses rather than merely slower wealth gains.

9 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:

$$\begin{aligned} Opioid\ Prescriptions_{p,t} =& \beta_1 Home\ Price\ Growth_{z,t-1} \times Indicator_{p(,t)} + \\ & \beta_2 Home\ Price\ Growth_{i,t-1} + \beta_3 Indicator_{p(,t)} + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \end{aligned} \tag{3}$$

where p denotes the provider, 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.

9.1 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 7.

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 3, 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 -0.58, while the coefficient on the standalone *Provider Home Price Growth* is -0.38. 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.

In Columns (3)-(4), we replace *Provider Home Price Growth* with the indicator for providers' house price growth in the bottom decile. The implications are similar. Providers whose house price growth falls within the bottom decile subsequently increase their opioid prescriptions by 8-9% more in more competitive markets.

9.2 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 3, 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.[29]

The results in Table 8 support our hypothesis. The coefficients on *Provider House*

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

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 12% (=(1.70+0.30)×0.06)—6.7 times the 1.8% increase (=0.30×0.06) observed among other providers. This stark difference in sensitivity to housing wealth shocks provides evidence that financial considerations influence prescribing behavior.

In Columns (3)-(4), we replace *Provider Home Price Growth* with the indicator for providers' house price growth in the bottom decile. The implications are similar. Nurse practitioners whose house price growth falls within the bottom decile increase their opioid prescriptions by 36% (=exp(0.305)-1).

9.3 Stronger Effects among Providers Serving Low-Income or Low-Education 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. Prior research has established that individuals with lower income and education levels face higher risks of opioid addiction and overdose deaths.[30] 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.

In Column (1), we estimate Equation 3 with the *Indicator* being *ZIP Low Income*, which equals one for office ZIP codes in the bottom quintile of household median income. Column (2) 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 signif-

[30]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).

icant in all four columns. The results suggest that when experiencing slow house price growth, providers increase opioid prescriptions by more if they serve low-income or low-education patients. Among providers practicing in low-income or low-education ZIP codes, their opioid prescription response to their house price growth is 2.7 times (=-0.850/-0.316) or 81% (=-0.351/-0.431) larger than those in other areas, respectively.

In Columns (3)-(4), we replace *Provider Home Price Growth* with the indicator for providers' house price growth in the bottom decile. The implications are similar. When providers' house price growth falls within the bottom decile, providers working in low-income or low-education ZIP codes increase their opioid prescriptions by 13% or 5.5% more relative to other providers, respectively.

9.4 Stronger Effects Prior to Policy Intervention

To address opioid overprescription, states implemented various regulatory measures, with the most prominent being pill mill laws, prescription drug monitoring programs (PDMPs), and prescribing limits (Finkelstein et al., 2025). We hypothesize that physicians' financial health has a diminished effect on prescribing behavior following the implementation of these policies. Using the year a state first adopted any of these three measures as the event year, we employ a stacked difference-in-differences approach (Gormley and Matsa, 2011)[31] to examine how physicians' house price growth influences their opioid prescribing patterns before and after policy implementation. Figure A1 plots the coefficients for each year between three years before and after the event year, controlling for provider fixed effects and the practice city–year fixed effects. The estimates reveal that the effect is concentrated in the pre-policy period and becomes both economically small and statistically insignificant following policy adoption. These findings provide suggestive evidence that state opioid regulations reduced the influence of physicians' financial pressures on their prescribing

[31]Baker et al. (2022) suggest that researchers use one of three methods, including the stacked difference-in-differences approach, in a staggered event setting.

decisions.

10 ADHD Drug Prescription

In this section, we extend our analysis of opioid prescription to drugs used to treat ADHD. Recent reports have uncovered the abuse in ADHD drug prescriptions.[32] Since such drugs have gained more attention since 2013 among potential recipients (Zhao et al., 2022), we focus on the sample period of 2013 and later. Table 10 repeats our main analyses on opioid prescription (Table 3), replacing the dependent variable with the provider-year level total ADHD drug costs in natural logs (Columns 1-5) and the share of ADHD drug costs relative to total prescribed drug costs (Column 6). Based on Column (5), where we control for provider fixed effects and office–year fixed effects, when providers experience a one-standard-deviation (4%) lower house price growth, they prescribe 5% more ADHD drugs. This result is also robust when we restrict to the sample of providers who live far away from the office. This parallel finding for ADHD drugs strengthens our central argument that providers' financial health influences their prescribing decisions across different categories of medications with misuse potential, validating the broader applicability of the documented behavioral channel.

11 Conclusion

To understand the impact of financial stress on professional judgment, we examine how healthcare providers' financial circumstances influence their prescribing decisions for medications with misuse potential. 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

[32] See, https://www.justice.gov/archives/opa/pr/founderceo-and-clinical-president-digital-health-company-arrested-100m-adderall-distribution.

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. While the opioid crisis has evolved, these historical effects provide crucial evidence of a fundamental behavioral channel—how providers' financial stress can compromise their professional judgment—a lesson vital for preventing future crises involving other drug classes.

Several patterns in our data suggest a causal interpretation of these findings and illuminate the underlying mechanism. The relationship intensifies in more competitive healthcare markets, suggesting that providers may use prescribing, particularly of potentially dependency-inducing medications, as a tool for patient retention when experiencing slower growth in personal wealth. 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 exhibit 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 analysis also provides evidence that policy interventions can mitigate these concerning patterns. Using a stacked difference-in-differences approach, we find that state-level opioid regulations—including pill mill laws, prescription drug monitoring programs, and prescribing limits—successfully reduced the influence of physicians' financial pressures on their prescribing decisions. The effect of financial stress on opioid prescribing is concentrated in the pre-policy period and becomes both economically small and statistically insignificant following policy adoption.

Our findings reveal important insights into how financial health affects professional

conduct. In particular, they have important implications for healthcare policy and public health broadly, especially in preventing future medication-related crises, but also for the design of incentive structures and ethical guidelines in other professional domains where personal financial pressures could compromise judgment. They reveal a previously undocumented channel—providers' personal financial circumstances—through which economic conditions can affect prescribing patterns for medications with misuse potential. Since the effect is amplified in competitive healthcare markets, policymakers should carefully consider the potential tension between market pressures and public health interests. Our results suggest that policies aimed at addressing medication misuse and related harms may need to pay special attention to vulnerable populations and the providers who serve them.

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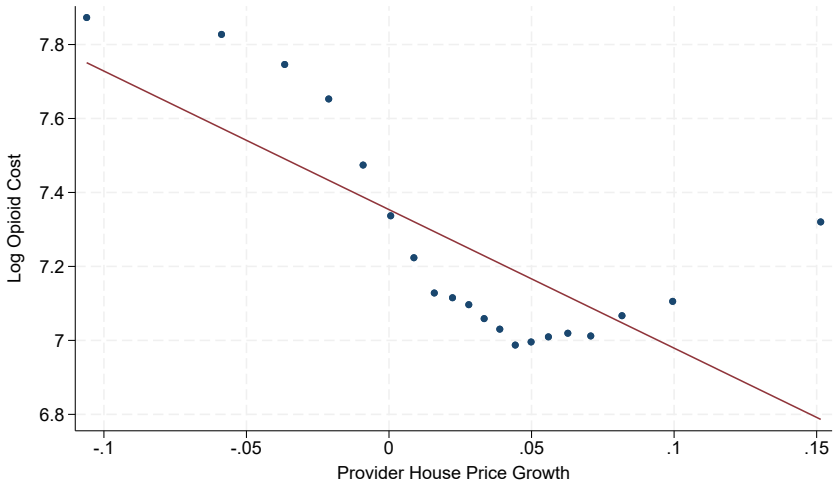
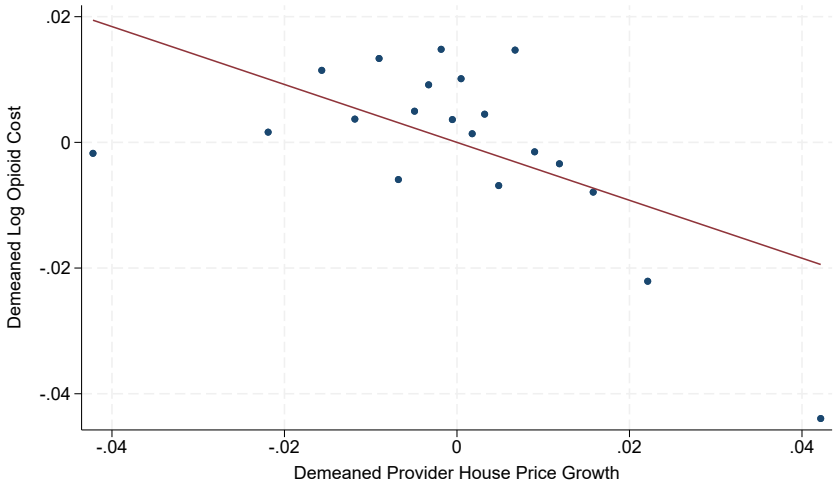
Figure 1: Opioid Prescriptions vs Provider House Price Growth

(a) Using Raw Variables

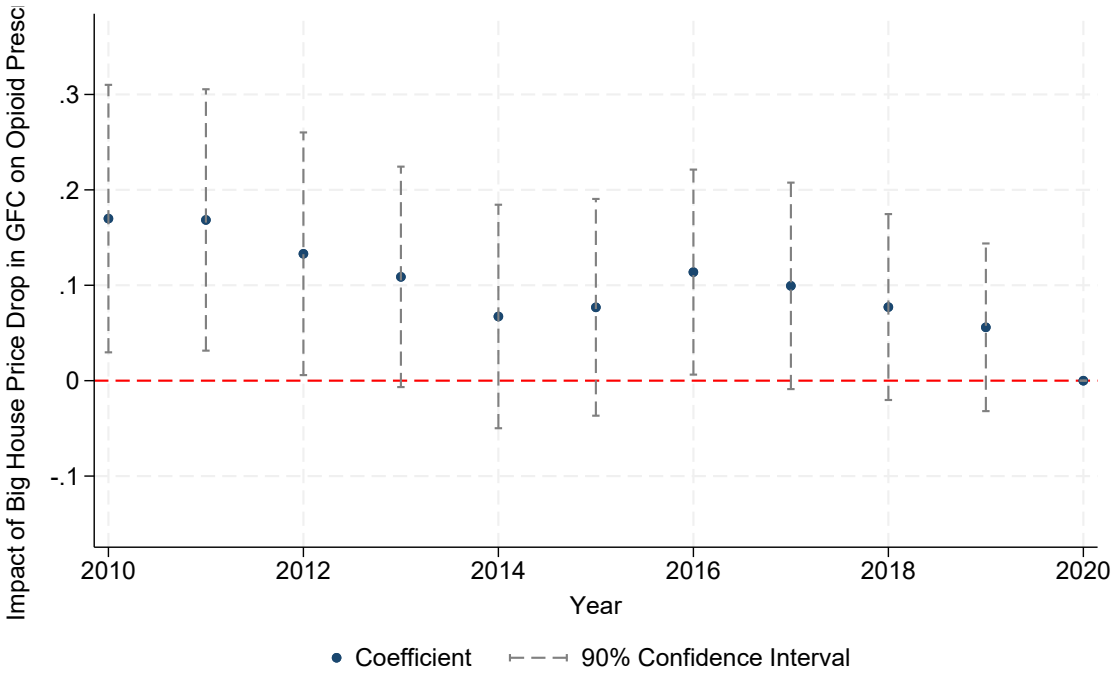


(b) Using Demeaned Variables



These figures present binscatter plots depicting the relation between healthcare providers' financial conditions and the amount of opioids they prescribe. 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 previous year. The y-axis indicates *Log Opioid Cost*, the natural logarithm of one plus the cost of opioids prescribed. Panel (a) presents the plot using raw variables. Panel (b) presents the plot using demeaned variables after removing provider and office ZIP–year fixed effects.

Figure 2: 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 2:

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

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. We control for provider fixed effects and ZIP–year fixed effects. We plot the estimated coefficients and the corresponding 90% confidence intervals. Standard errors clustered at the provider level.

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
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
ADHD Cost	1,110.44	2,679.80	0.00	0.00	896.95
Log ADHD Cost	3.18	3.60	0.00	0.00	6.80
ADHD Cost/ALL Drug	0.01	0.04	0.00	0.00	0.00

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 previous year. *(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 Lagged Opioid Prescrition Positively Correlated with Services and Charges

	Log # Services		Log Submitted Charges	
	(1)	(2)	(3)	(4)
Log Opioid Cost	0.036***	0.033***	0.036***	0.033***
	(23.78)	(22.03)	(23.36)	(21.49)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	6.171	6.177	11.260	11.267
Y SD	1.006	1.004	1.046	1.043
X Mean	6.606	6.612	6.606	6.612
X SD	3.118	3.117	3.118	3.117
N	343,234	337,181	343,234	337,181

This table examines how providersâ services delivered and charges submitted are related to their opioid prescriptions in the previous year. The dependent variable is the log amount of services delivered in Columns (1)-(2) and the log amount of charges submitted in Columns (3)-(4).To reduce the effect of the number of working days on these outcome variables, we scale the raw services and charges by the number of actual days worked and multiply them by 260. The independent variable is providersâ log opioid prescription in the previous year, measured in dollar cost. We control for provider fixed effects in all specifications. In addition, we include office city–year fixed effects in Columns (1) and (3), and office ZIP–year fixed effects in Columns (2) and (4), with *Office* referring to the providerâs office Placekey ID, the identifier for a physical place. *t*-statistics, reported in parentheses, are based on standard errors clustered at the provider level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Table 3: Provider Home Price Growth Affects Opioid Prescription

	Log Opioid Cost					Short-Acting	Opioid/All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Provider Home Price Growth	-0.536***	-0.461***	-0.532***	-0.499***	-0.469***	-0.493***	-0.027***
	(-4.35)	(-3.75)	(-3.12)	(-3.85)	(-2.84)	(-3.61)	(-4.81)
Sample Restriction			Home Far to Office				
Provider FE	Y	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y					Y	Y
Office Zip × Year FE		Y	Y				
Office Zip × Specialty × Year FE				Y			
Office × Year FE					Y		
Y Mean	7.252	7.260	7.147	7.331	7.440	6.885	0.057
Y SD	2.678	2.674	2.690	2.619	2.501	2.737	0.131
X Mean	0.027	0.027	0.028	0.027	0.027	0.027	0.027
X SD	0.057	0.057	0.056	0.057	0.056	0.056	0.057
N	624,483	616,560	290,684	565,759	373,339	464,763	624,483

This table presents tests that examine the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 1. In Columns (1)-(5), the dependent variable is *Log Opioid Cost*, the natural logarithm of one plus the cost of opioids prescribed. In Column (6), the dependent variable is the natural log of short-acting opioid drug prescription in terms of costs. In Column (7), the dependent variable is the ratio of opioid prescription relative to total drug prescription in terms of total costs. The main independent variable is *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 previous year. All columns include provider fixed effects. In addition, Columns (1), (6), and (7) also include providers' office city–year fixed effects. Column (2) also includes providers' office ZIP–year fixed effects. Column (3) uses a subsample of providers with distances between home and offices that are greater than the sample median. Column (4) includes providers' office ZIP-by-specialty–year fixed effects. Column (5) includes providers' office–year 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: Provider Home Price Growth Affects Business Volume and Charges

	Log # Service		Log Submitted Charge	
	(1)	(2)	(3)	(4)
Provider Home Price Growth	-0.104**	-0.097**	-0.080*	-0.081*
	(-2.48)	(-2.32)	(-1.80)	(-1.84)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	6.065	6.070	11.167	11.172
Y SD	1.049	1.047	1.092	1.090
X Mean	0.045	0.045	0.045	0.045
X SD	0.042	0.042	0.042	0.042
N	480,683	474,788	480,683	474,788

This table examines the relationship using the same Medicare Part B data employed in our earlier business volume analysis. The dependent variables are the log amounts of services delivered (Columns 1-2) and charges submitted (Columns 3-4). The main independent variable is *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 previous year. We maintain provider fixed effects throughout, with location controls progressing from office city–year to office ZIP–year fixed effects. *t*-statistics, reported in parentheses, are based on standard errors clustered at the provider level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Table 5: Provider Home Price Growth Affects Opioid-Related Payment from Pharma to Provider

	1(Opioid Payment)		Log(Opioid Payment)	
	(1)	(2)	(3)	(4)
Provider Home Price Growth	-0.096***	-0.080**	-0.251**	-0.197*
	(-3.26)	(-2.54)	(-2.43)	(-1.80)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	0.122	0.122	0.419	0.421
Y SD	0.327	0.328	1.161	1.164
X Mean	0.046	0.046	0.046	0.046
X SD	0.043	0.043	0.043	0.043
N	281,646	275,169	281,646	275,169

This table examines the effect of healthcare providers' financial condition on the amount of opioid-related payments they receive from pharmaceutical companies. In Columns (1) and (2), the dependent variable is an indicator for whether the provider receives such payments. In (3) and (4), the dependent variable is the natural log of such payments plus one. *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 previous 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 6: Effect on Opioid Prescription When Provider's Home Price Growth is Negative

	Log Opioid Cost			
	(1)	(2)	(3)	(4)
1(Provider Home Price Growth Bottom 10%, <-4%)	0.035**	0.032**		
	(2.49)	(2.24)		
Provider Home Price Growth (<0)			-0.766***	-0.677***
			(-3.40)	(-3.00)
Provider Home Price Growth (≥0)			-0.410***	-0.344**
			(-2.59)	(-2.15)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	7.252	7.260	7.252	7.260
Y SD	2.678	2.674	2.678	2.674
Provider Home Price Growth Mean in Bottom 10%	-0.080	-0.080		
Provider Home Price Growth SD in Bottom 10%	0.029	0.029		
Provider Home Price Growth (<0) Mean			-0.012	-0.012
Provider Home Price Growth (<0) SD			0.027	0.027
Provider Home Price Growth (>=0) Mean			0.039	0.038
Provider Home Price Growth (>=0) SD			0.040	0.040
N	624,483	616,560	624,483	616,560

In Columns (1)-(2), we test whether any negative home price growth between 2009 and 2019 influences opioid prescriptions in the following year. The dependent variable remains the natural log of prescribed opioid costs. Our key independent variable is an indicator for whether the previous year's house price growth in the provider's residential ZIP code fell within the bottom decile of our sample. This bottom decile experience a maximum price change of -4.27% and a mean of -7.93%. In Columns (3)-(4), we employ a spline specification to separately estimate the effects of positive and negative price changes. Specifically, we replace the *Provider Home Price Growth* measure in Table 3 with two independent variables. The first one, *Provider Home Price Growth (<0)*, equals the raw home price growth measure when negative and zero otherwise. The second one, *Provider Home Price Growth (≥0)* equals the raw home price growth measure when non-negative 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 with Provider Competition

	Log Opioid Cost			
	(1)	(2)	(3)	(4)
Provider Home Price Growth × High Competition	-0.580*	-0.343		
	(-1.94)	(-1.13)		
Provider Home Price Growth	-0.384***	-0.378***		
	(-2.81)	(-2.76)		
1(Provider Home Price Growth Bottom 10%, <-4%) × High Competition			0.091***	0.081**
			(2.60)	(2.29)
1(Provider Home Price Growth Bottom 10%, <-4%)			0.013	0.014
			(0.84)	(0.87)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	7.252	7.260	7.252	7.260
Y SD	2.678	2.674	2.678	2.674
X Mean	0.027	0.027	0.107	0.107
X SD	0.057	0.057	0.309	0.309
N	624,351	616,426	624,351	616,426

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 3. *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 previous year. We construct a Herfindahl-Hirschman Index (HHI) at the city-year 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 8: Effect on Opioid Prescription is Stronger for Nurse Practitioners

	Log Opioid Cost			
	(1)	(2)	(3)	(4)
Provider Home Price Growth × Nurse Practitioner	-2.071***	-1.703***		
	(-7.39)	(-5.95)		
Provider Home Price Growth	-0.358***	-0.303**		
	(-2.82)	(-2.38)		
1(Provider Home Price Growth Bottom 10%, <-4%) × Nurse Practitioner			0.370***	0.305***
			(7.01)	(5.72)
1(Provider Home Price Growth Bottom 10%, <-4%)			0.010	0.010
			(0.70)	(0.68)
Provider FE	Y	Y	Y	Y
OfficeCity × Year FE	Y		Y	
OfficeZip × Year FE		Y		Y
Y Mean	7.251	7.259	7.251	7.259
Y SD	2.679	2.675	2.679	2.675
X Mean	0.027	0.027	0.107	0.107
X SD	0.057	0.057	0.309	0.309
N	601,927	594,349	601,927	594,349

This table examines the heterogeneous effect of healthcare providers' financial condition on opioid prescriptions between nurse practitioners and other providers, estimated using Equation 3. *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 previous year. *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 9: Effect on Opioid Prescription is Stronger for Vulnerable Patients

	Log Opioid Cost			
	(1)	(2)	(3)	(4)
Provider Home Price Growth × ZIP Low Income	-0.850***			
	(-4.56)			
Provider Home Price Growth × ZIP Low Education		-0.351*		
		(-1.82)		
1(Provider Home Price Growth Bottom 10%, <-4%) × ZIP Low Income			0.130***	
			(4.19)	
1(Provider Home Price Growth Bottom 10%, <-4%) × ZIP Low Education				0.055*
				(1.71)
Provider Home Price Growth	-0.316**	-0.431***		
	(-2.44)	(-3.34)		
1(Provider Home Price Growth Bottom 10%, <-4%)			0.005	0.021
			(0.34)	(1.38)
ZIP Low Income	-0.051		-0.087**	
	(-1.29)		(-2.24)	
ZIP Low Education		0.019		0.003
		(0.41)		(0.07)
Provider FE	Y	Y	Y	Y
OfficeCity × Year FE	Y	Y	Y	Y
Y Mean	7.257	7.256	7.257	7.256
Y SD	2.677	2.677	2.677	2.677
X Mean	0.027	0.027	0.107	0.107
X SD	0.057	0.057	0.310	0.310
N	619,528	620,511	619,528	620,511

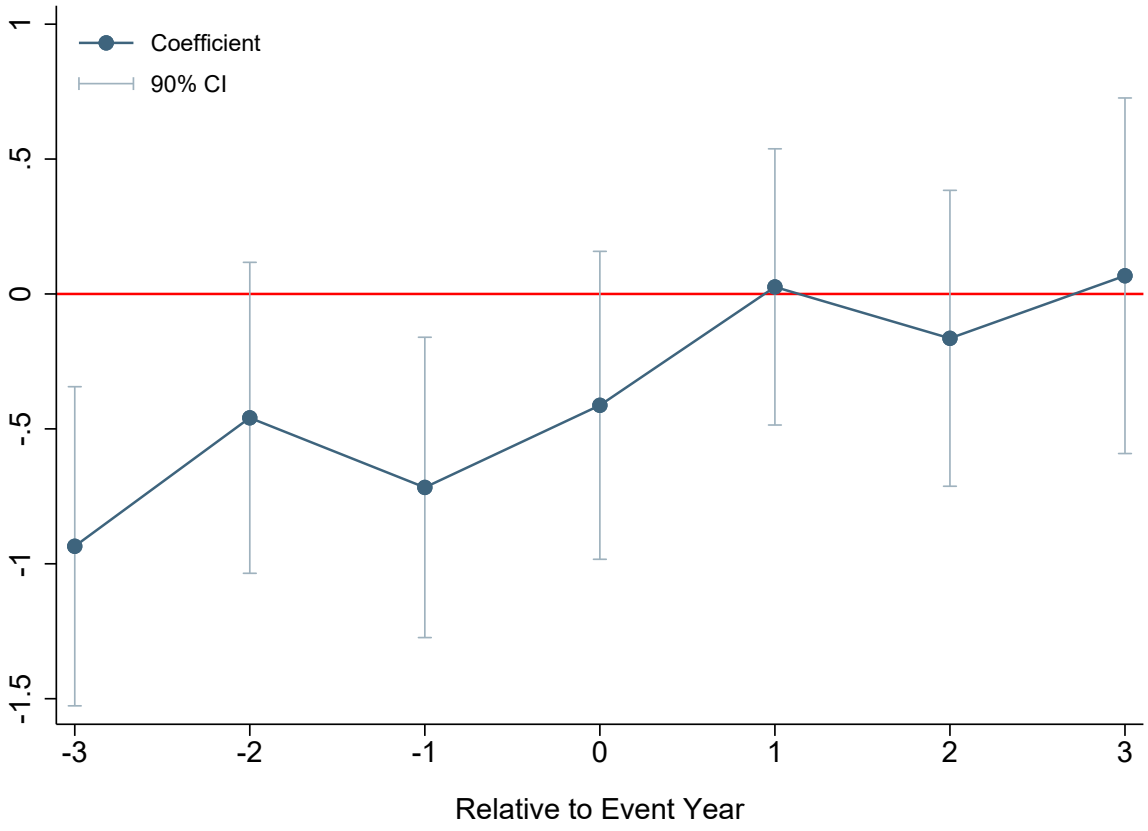
This table examines the heterogeneous effect of healthcare providers' financial condition on opioid prescriptions between low-income (or low-education) ZIP codes, estimated using Equation 3. *Provider Home Price Growth* is the annual growth rate of the provider's home price, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the previous year. *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's 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.

Table 10: Provider Home Price Growth Affects ADHD Prescription

	Log ADHD Cost					ADHD Cost/All Drug
	(1)	(2)	(3)	(4)	(5)	(6)
Provider Home Price Growth	-0.753**	-0.999***	-1.390***	-1.540***	-1.294**	-0.006*
	(-2.21)	(-2.77)	(-2.66)	(-3.64)	(-2.13)	(-1.78)
Sample Restriction			Home Far to Office			
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y					Y
Office Zip × Year FE		Y	Y			
Office Zip × Specialty × Year FE				Y		
Office × Year FE					Y	
Y Mean	3.182	3.193	3.186	3.212	3.145	0.007
Y SD	3.605	3.607	3.599	3.610	3.589	0.036
X Mean	0.045	0.045	0.045	0.045	0.044	0.045
X SD	0.041	0.041	0.041	0.041	0.040	0.041
N	255,287	248,307	113,753	215,239	126,005	255,287

This table presents tests that examine the effect of healthcare providers' financial condition on the amount of ADHDs they prescribe, estimated using Equation 1. In Columns (1)-(5), the dependent variable is *Log ADHD Cost*, the natural logarithm of one plus the cost of ADHDs prescribed. In Column (6), the dependent variable is the share of ADHD drug costs relative to total prescribed drug costs. The main independent variable is *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 previous year. All columns include provider fixed effects. In addition, Columns (1) and (6) also includes providers' office city–year fixed effects. Column (2) also includes providers' office ZIP–year fixed effects. Column (3) uses a subsample of providers with distances between home and offices that are greater than the sample median. Column (4) includes providers' office ZIP-by-specialty–year fixed effects. Column (5) includes providers' office–year 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.

Figure A1: Effect of Provider House Price Growth on Opioid Prescription Before and After Policy Intervention



This figure shows coefficient estimates from a stacked difference-in-differences regression examining the relationship between physicians' house price growth and opioid prescribing behavior. The event year (0) represents when a state first adopted pill mill laws, PDMPs, or prescribing limits, following the timing in Finkelstein et al. (2025). Estimates are shown for years relative to policy implementation, with 90% confidence intervals. We control for provider fixed effects and their practice city–year fixed effects. Standard errors are corrected for clustering at the provider level.

Table A1: Provider Home Price Growth Affects Opioid Prescription: Robustness

	Log Days Supply	Log Claims	Log Recipient #	1(Opioid>0)
	(1)	(2)	(3)	(4)
Provider Home Price Growth	-0.499***	-0.343***	-0.217***	-0.045***
	(-4.28)	(-4.71)	(-3.40)	(-3.13)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y	Y	Y	Y
Y Mean	7.136	4.395	3.512	0.936
Y SD	2.470	1.716	1.266	0.245
X Mean	0.027	0.027	0.047	0.029
X SD	0.057	0.057	0.043	0.055
N	624,483	624,483	413,127	708,688

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. The dependent variables are the opioid prescription amounts: *Log Opioid Days Supply*; *Log Opioid Claims*; *Log Opioid Recipient #*, which is the natural logarithm of one plus the number of patients receiving opioid prescriptions; and *1(Opioid>0)*, an indicator that equals one if the provider prescribes any opioid in that year.The main independent variable is *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 previous 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.