How Do Financial Conditions Affect Professional Conduct? Evidence from Opioid Prescriptions

Isil Erel, Shan Ge, Pengfei Ma*

Can personal finances affect professional conduct? We find that healthcare providers increase opioid prescriptions when experiencing negative home value shocks—a proxy for wealth shocks. Results are robust to provider office-year fixed effects and to using providers who live far from their offices, largely ruling out patient-demand explanations. Effects are stronger among lower-income providers and those treating low-income and minority patients. Higher opioid prescription ratios correlate with increased future business volume and pharmaceutical payments. Similar patterns emerge for ADHD medications. Our findings offer novel insights into professional conduct under financial pressure, with implications extending beyond healthcare.

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

Keywords: Professional conduct, opioid, ADHD, prescription, healthcare provider, real estate, financial conditions, wealth shock, ethics

*Isil Erel, Ohio State University, erel@fisher.osu.edu, NBER, and ECGI; Shan Ge, New York University, sg3634@stern.nyu.edu; Pengfei Ma, Singapore Management University, pengfeima@smu.edu.sg. We thank Douglas Almond, Marika Cabral, Serdar Dinc, Ruediger Fahlenbrach, Will Gerken, David Matsa, Ryan McDevitt, Giang Nguyen, Jordan Nickerson, Molly Schnell, as well as conference participants at the UNSW Corporate Finance Conference, OSU Alumni Conference, FRA Conference, and UT Dallas Finance Conference. Dongyu Zuo provided excellent research assistance.

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 their decisions directly impact patient health outcomes. Studying how healthcare providers' personal financial circumstances affect their clinical choices has critical implications for healthcare policy and patient protection. Although our study focuses on healthcare, the mechanisms by which financial pressure influences professional conduct are likely generalizable to a wide array of fields, in which conflicts of interest between personal financial gain and client welfare may arise.

This study examines whether healthcare providers' financial conditions affect their drug prescribing behavior. We focus on opioid prescriptions, as the opioid crisis represents a significant public health challenge, with recent policy changes potentially exacerbating the epidemic.[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 or medical practices.

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 the healthcare provider's practice office city- or office 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, where offices are identified by the unit/suite number (when available), street number,

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

street name, city, and ZIP code. The result is also robust when restricting the sample to providers who live far from their offices. Thus, it is unlikely that patients' demand drives our results.

This result is consistent with the idea that, when faced with a negative wealth shock, providers prescribe more opioids, possibly to encourage 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 84% of primary care doctors and 93% of specialists; when volume-based incentives are included in compensation plans, they account for more than two-thirds of providers' compensation (Reid et al., 2022). Moreover, increasing service volume 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 patient visits. By prescribing opioids, providers may increase patient volume by attracting patients who seek opioids and serving opioid-addicted repeat visitors. Indeed, our analysis suggests that when providers prescribe more opioids, they receive more patient visits and submit more charges to Medicare in the following year.

There is another channel through which providers can benefit financially from opioid prescriptions. According to Schneider et al. (2022), 77% of healthcare facilities conduct patient satisfaction surveys, and 22% incorporate these results into provider compensa-

tion 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 driven by 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 changes in house prices 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 wealth. 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 them to purchase 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 (Brown and Matsa, 2020; Bernstein, 2021), risk-taking behavior (Pool et al., 2019), consumption patterns (Campbell and Cocco, 2007; Aladangady, 2017; Berger et al., 2017; Agarwal, 2007), and local retail markups (Stroebel and Vavra, 2019).

From a research design perspective, house 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 comprises 263,281 providers across all states, spanning from 2010 to 2020. Our analysis yields the following 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: when the change in house prices decreases from the 90th to the 10th percentile (13.2 percentage points), providers prescribe 4.3% more opioids. Importantly, this effect is not driven by a general increase in prescriptions of all drugs—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.

Our second key finding indicates that less favorable changes in house prices are associated with increased patient visits and higher charges submitted to Medicare in the following year. Quantitatively, when house price changes decrease from the 90th to the 10th percentile, providers increase patient visits and total Medicare charges by 1.9%, considering the combined effect in the following and subsequent years. Assuming providers' compensation scales with patient visits and submitted charge amounts, this represents a meaningful increase in their earnings.

This observed pattern aligns with our hypothesis that when healthcare providers experience adverse house price shocks, they seek to boost their compensation by increasing service volume. This could be achieved either by intensifying their overall practice or by leveraging opioid prescriptions to attract more patient visits, as well as by pursuing

other strategies to enhance their earnings. One might interpret our results as implying that providers prescribe closer to the optimal level when their house price growth slows. However, it is improbable that providers systematically under-prescribe opioids when experiencing favorable house price changes and only approach optimal levels when their financial conditions deteriorate.

Third, we find that providers experiencing adverse house price changes are more likely to receive payments related to opioids from pharmaceutical companies. 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. When providers experience a decrease in house price changes from the 90th to the 10th percentile, their probability of receiving opioid-related payments increases by 4% relative to the baseline. 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 house price declines during the 2007-2009 financial crisis period increased their opioid prescriptions (scaled by all drug prescriptions) by approximately 5.8% more in 2010-2012 compared to providers working in the same ZIP code but residing in other areas. This difference diminished after 2012, possibly due to the recovery of the housing market. In addition, we find that when providers experience a change in house prices in the bottom decile or mortgage foreclosures outside the GFC, their opioid prescriptions increase by 2.4% to 5.5% in the following year.

In addition, if financial considerations drive prescribing behavior, the effects should be stronger among providers with lower labor income, whose net worth is more heavily concentrated in housing. We test this hypothesis by matching providers to occupation-

location-year-level income data from the Bureau of Labor Statistics and controlling for local cost-of-living differences using Bureau of Economic Analysis price parities. The results confirm that lower-income providers respond more strongly to house price declines: providers with income one standard deviation below the median show effects approximately 2.3 times larger than those at the median, providing additional support for the hypothesis that providers increase opioid prescribing when their financial conditions deteriorate.

Moreover, we find that the relationship between providers' financial stress and opioid prescriptions is stronger among providers serving more vulnerable populations. Specifically, providers practicing in low-income ZIP codes and those treating higher proportions of minority patients 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.

Furthermore, we exploit the variations in the regulation of opioid prescriptions. To address opioid overprescription, states implemented a must-access provision to the prescription drug monitoring programs (PDMPs), which requires providers to check patients' prescription history before prescribing controlled substances. The requirement has been shown to reduce opioid prescriptions (Wen et al., 2019). Using a stacked difference-in-differences approach, we find that the influence of providers' house price changes 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. However, the policy crackdown on opioid prescriptions may shift providers towards prescribing other harmful medications that can develop

dependency.[2]

Finally, we extend our analyses to ADHD medications, which also have significant potential for misuse and have been subject to anecdotal reports of inappropriate prescribing. Focusing on the sample period from 2013 onward, a period when ADHD drugs gained increased attention among potential recipients (Zhao et al., 2022), we find a similar pattern to that observed with opioids: providers increase their prescription of ADHD drugs when they experience relatively worse house price changes. 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 the fact that opioid side effects are particularly severe for older adults (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 regula-

[2]See an example of such medication `https://www.wsj.com/health/gabapentin-painkiller-hidden-risks-603e6130`.

tory 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 the overprescription of opioids and other addictive medications. More broadly, compensation reform can mitigate incentives for unnecessary medical services, reduce wasteful medical spending, and promote patient health.

Finally, our findings suggest that financial pressure may disproportionately compromise the quality of care for low-income and minority patients, who face heightened susceptibility to opioid addiction and its associated harms (Altekruse et al., 2020; Friedman et al., 2019; Nestvold et al., 2023). 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 potentially applicable in fields beyond healthcare, 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 clients or increase profits, potentially compromising client interests. Employers and regulators should monitor professional conduct more closely during negative local or sectoral shocks and 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 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 reflects advisors working more or becoming more prone to misconduct. We demonstrate that providers specifically increased their opioid prescriptions as a proportion of their total drug prescriptions following adverse house 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).

We also distinguish our paper by examining whether personal wealth shocks affect healthcare providers who have 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) finds that physicians' lower housing returns are associated with more C-section surgeries, providing complementary evidence.[3]

Second, we contribute to the literature examining the relationship between healthcare providers' financial incentives and their clinical choices. A number of studies document a positive correlation between payments received by providers from pharmaceutical companies and their opioid prescriptions.[4] 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., reimburse-

[3]Our paper is also related to work on misconduct in the healthcare industry, including Griffin and Priest (2024), and more broadly, the literature on professional misconduct (Dimmock and Gerken, 2012; Mullainathan et al., 2012; Dimmock et al., 2018; Egan et al., 2019; Egan, 2019; Egan et al., 2022; Dimmock et al., 2025; Clifford et al., 2025).

[4]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), and Nguyen et al. (2019).

ment rates, liabilities) affect providers' service supply.[5] 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. Most relevant to this paper are studies that find providers' pay schemes are associated with opioid prescriptions (Meinhofer and Witman, 2018; Cher et al., 2019). In the finance literature, Ouimet et al. (2023) find that opioid prescriptions reduce employment and establishment growth. 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 effects on local innovation activities.

We contribute by revealing that providers' personal financial conditions—rather than payments or market-level competition—can affect their prescribing decisions for medications with potential for misuse.[6] 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 shifts in professional conduct that compromise service quality or client welfare.

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,

[5] See Matsa (2007), Hackmann et al. (2024), Alexander and Schnell (2024), Einav et al. (2018), Clemens and Gottlieb (2014), Batty and Ippolito (2017), Gruber and Owings (1994), Yip (1998), and Jacobson et al. (2006, 2010, 2013).

[6] 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) and the literature on healthcare and finance (Gupta et al., 2024; Liu, 2022; Howell and Liu, 2023; Aghamolla et al., 2023; Adelino et al., 2015; Cornaggia et al., 2024, 2025; Gao et al., 2025; Al-Sabah and Ouimet, 2021; Gao et al., 2022; Gallagher et al., 2019; Li and Tong, 2025; Tong, 2021).

particularly OxyContin, leading to a surge in opioid use and misuse (Dasgupta et al., 2018). Prescription opioid sales quadrupled between 1999 and 2008.[7] Between 2001 and 2016, the percentage of all deaths attributable to opioids 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. Florence et al. (2021) estimate that in 2017 alone, the economic cost of opioid use disorder and overdose deaths was estimated at nearly $1.02 trillion. The crisis has led to decreased life expectancy in the United States, with 217 people dying each day from opioid overdoses in 2023.[8] The COVID-19 pandemic subsequently exacerbated the opioid crisis, with drug overdose deaths increasing dramatically during and after the pandemic. According to CDC data, opioid overdose deaths increased by 38% nationally in 2020.[9]

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.[10] Other major settlements include agreements with Johnson & Johnson, pharmaceutical distributors, and pharmacy chains, amounting to more than $39 billion.[11]

To curb the overprescription of opioids, states established Prescription Drug Monitoring Programs (PDMPs), among other efforts. These programs created databases on patients' current or past use of controlled substances. Initially, access to this database before pre-

[7] https://www.cdc.gov/mmwr/preview/mmwrhtml/mm6043a4.htm.

[8] https://www.cdc.gov/overdose-prevention/about/understanding-the-opioid-overdose-epidemic.html.

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

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

[11] https://www.naag.org/issues/opioids/ and https://www.bmj.com/content/379/bmj.o2688.

scribing opioids was voluntary for medical providers. However, this voluntary access led to only a small fraction of providers accessing the information. In response, 33 states shifted to a must-access system between 2012 and 2019. This mandated review of controlled substance prescription history helps providers identify high-risk patterns (such as those with multiple prescriptions from different providers) and increases the risk of providers facing lawsuits, thereby discouraging inappropriate prescribing. Despite these efforts, drug overdose deaths, a significant fraction of which involve prescribed opioids, remain a leading cause of injury mortality in the U.S.[12]

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 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). Healthcare providers are assigned a unique National Provider Identifier (NPI) issued by CMS. Once assigned, an NPI remains the same, even if the provider changes their name, address, or other information. Importantly, healthcare providers with active NPIs cannot opt out or request suppression of their records. We obtain monthly downloadable files from January 2007 to March 2023 to construct panel data on providers. The data include the provider's NPI, first/middle/last name, gender, taxonomy group, practice location address, and mailing address.[13] We then geolocate providers' practice loca-

[12] https://www.cdc.gov/overdose-prevention/about/understanding-the-opioid-overdose-epidemic.html

[13] The data are downloaded from https://download.cms.gov/nppes/NPI_Files.html. The webpage provides a link to the most recent monthly file, while earlier monthly files can be accessed by changing the

tions using Placekey (`www.placekey.io`) to obtain the latitude, longitude, and an identifier for the practice address, which uniquely identifies the unit/suite number (when available), street number, street name, city, and ZIP code.

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 1980s, with more than 850 million historical real estate transactions from over 3,000 County Clerk/Recorder offices. The data provide important information on the property address, buyer and seller names, transaction date and price, and property characteristics. Moreover, CoreLogic has processed the data to generate valuable information, such as parsing names into first, middle, and last names, and geolocating addresses to obtain the property's latitude and longitude.

CoreLogic data have been widely used in the literature to identify individuals' properties, e.g., 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 records based on the provider's name and calculate the distance between the provider's practice location and the property using the addresses' latitudes and longitudes. 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 an annual frequency. Specifically, we consider a provider to own a property in a given year if it was purchased before that year and was 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 given year to determine home ownership.

We obtain the ZIP code-level Zillow Home Value Index (ZHVI) at a monthly frequency from Zillow. The data are available to us from January 2001 until the end of July 2022.

month and year in the download URL.

This dataset has been widely used in the literature to capture house 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 prescription drugs for 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 have been available since 2013. Because our version of the CoreLogic data is available only through February 2021, we cannot verify providers' homeownership information for 2021 and later. Thus, 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. 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 treat observations with suppressed values as missing in our analysis and drop them from the regressions. In a robustness analysis, we define a dummy variable, *1(Opioid>0)*, indicating whether the provider prescribes opioid drugs, and set it to one if the opioid prescription quantity is greater than 0, including suppressed cases. Analysis using *1(Opioid>0)* includes all the observations.

We further obtain the 2010-2012 Part D data from ProPublica, a nonprofit investigative journalism organization that obtained the data from CMS under the FOIA.[14] 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 and obtain the provider's opioid prescription information. However, the ProPublica data report only providers with more than 10 prescriptions for a

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

drug in a year and do not include information on beneficiary counts or beneficiary demographics and health characteristics.

3.4 Other Datasets

We supplement our analyses with several additional datasets. To examine heterogeneous effects by provider income, we match providers to lagged occupation-location-year-level income data from the Bureau of Labor Statistics (BLS). The BLS occupations are detailed (e.g., nurse practitioners, family medicine physicians). To facilitate the match, we first link providers' office ZIP codes to counties using the crosswalk from the U.S. Department of Housing and Urban Development (HUD), and then link counties to metropolitan and nonmetropolitan areas in the BLS data using the BLS crosswalk. Because the mapping from ZIP codes to BLS areas is not one-to-one, we average income at the occupation-ZIP-year level when a ZIP code corresponds to multiple areas. We also match providers to lagged CBSA-year-level Regional Price Parities from the Bureau of Economic Analysis (BEA) to proxy for the cost of living, linking office ZIP codes to CBSAs using HUD's crosswalk. Similarly, we calculate averages when the matching is not one-to-one.

In other analyses, we match providers' prescriptions to the lagged median income of their office ZIP codes from the American Community Survey (ACS). The ACS ZIP-level data are estimates calculated using data collected over the preceding 60 months, available starting in 2011. For our analysis in Table 7, we match prescription data from 2010 and 2011 to the 2011 ACS data. In robustness tests (Table IA.7), we report results excluding this imputation, that is, using only the 2012 and later sample.

We also use CMS data on provider-year-level beneficiary demographics and health characteristics, including race and health risk scores. Using the racial composition of each provider's patients, we examine whether opioid prescribing responses to house price changes vary by providers' lagged non-white patient share. Because this information is available only from 2013 onward, we lack lagged non-white patient share for prescriptions

prior to 2014. In Table 7, we match prescriptions from years prior to 2014 to non-white patient share data from 2013. In robustness tests (Table IA.7), we report results excluding this imputation, that is, using only the 2014 and later sample.

In addition, we use data from Medicare Part B, which covers 80% of physician visit costs and accounts for 49% of the $1.01 trillion in Medicare spending in 2023.[15] This dataset provides provider-year level patient visit volumes and submitted charges. To eliminate the effect of the number of working days on the number of patient visits and submitted charges, we standardize the raw visits and charges by dividing them by the number of practice days and multiplying by 364.

Lastly, we obtain data on financial transfers from pharmaceutical firms to healthcare providers from the Sunshine Act Open Payments data, which are available since 2013. The act requires manufacturers to fully disclose payments of $10 or more made to providers (and teaching hospitals). Each record identifies the physician (via NPI), the associated drug, and the dollar value of the transfer. These transfers include cash and in-kind benefits such as meals, travel, and educational expenses. Prior research using this data finds that industry payments to providers are positively associated with the prescribing of the paying manufacturer's drugs (Agha and Zeltzer, 2022; Carey et al., 2021; Newham and Valente, 2024). In our analyses using this dataset, we include providers who appear at least once.

3.5 Sample

We begin with Medicare Part D data matched to NPPES and merge it with CoreLogic data to obtain property information for providers. We then merge it with Zillow data to obtain the change in house price at the property's ZIP code. In our main analysis, we include only providers who prescribed opioids at least once, but we remove this condition in robustness tests in Table IA.1. In the main sample, 76% of the providers have only one property, 17% have two, 5% have three, and 1% have more than three. We aggregate the data by taking

[15] https://www.kff.org/interactive/the-facts-about-medicare-spending/.

the simple average of house price changes for providers with multiple properties, yielding one observation per provider-year pair. Our main sample comprises 263,281 providers practicing in 12,841 ZIP codes, spanning from 2010 to 2020.

3.6 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% growth rate in house prices (0.03 in log difference). There are significant variations in house price changes, with a standard deviation of 6 percentage points, and the decline in house price changes from the 90th to the 10th percentile represents 13.2 percentage points.

Regarding providers' prescription of opioid drugs, on average, a provider's annual prescription of opioid drugs costs $6,237, totaling 3,340 days of supply and 155 claims. The opioid drug cost accounts for 12% of all drugs prescribed by the same provider.

4 Opioid Prescriptions Bring More Future Business

Our central hypothesis posits that providers' financial conditions influence their professional behavior, specifically opioid prescribing practices. This relationship rests on the assumption that providers who prescribe more opioids can increase business volume and income through greater patient retention and visits. To test this hypothesis, we use data on provider-year level patient visit volumes and submitted charges from Medicare Part B.

Table 2 examines how these business outcomes are related to providers' opioid prescriptions from the previous-year. Our dependent variables are the log of the number of patient visits (Columns 1-3) and the log of the dollar amount of charges submitted (Columns 4-6). The independent variable is providers' opioid prescriptions from the previous year. We measure this variable using two approaches: in Panel A, we calculate the ratio of opioid costs to total prescription costs for each provider-year, whereas in Panel B, we use the

natural logarithm of opioid costs.

We control for provider fixed effects in all specifications. In addition, we incorporate progressively more restrictive location-by-year controls: office city-by-year fixed effects in Columns (1) and (4), office ZIP-by-year fixed effects in (2) and (5), and office-by-year fixed effects in (3) and (6).

We control for lagged business volume to serve two purposes. First, it allows the variation in the lagged opioid prescriptions, the main independent variable in Panel B, to reflect providers' propensity to prescribe opioids rather than changes in overall business activity. Second, it accounts for the underlying trend in business growth, thereby mitigating the risk of a spurious association between business volume and lagged opioid prescriptions.

The estimated coefficients on lagged opioid prescriptions are consistently positive and statistically significant across all but two specifications. This result indicates that providers who prescribed more opioids in the previous year subsequently received more patient visits and submitted higher charges in the current year. Based on Columns (3) and (6) of Panel B, an increase in providers' lagged opioid prescriptions from the 10th to the 90th percentile corresponds to a 6.8% (9.745×0.007) and a 5.8% (9.745×0.006) increase in patient visits and charges submitted, respectively.

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 who are known to prescribe opioids more readily. Providers who accommodate these requests may cultivate patient loyalty that drives repeat visits.

Alternatively, the results in this section may arise from unobserved factors that simultaneously drive both increased opioid prescriptions and higher patient visits in subsequent periods. Our findings here provide suggestive support for the underlying assumption of

our main hypothesis: financial incentives may influence providers' professional behavior. We test this hypothesis in the following section.

5 Provider Financial Conditions Affect Opioid Prescriptions

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

$$Opioid\ Prescriptions_{p,t} = \beta Lag\ Provider\ House\ Price\ Change_{z,t-1} + \alpha_p + \alpha_{l,t} + \epsilon_{p,t}, \quad (1)$$

where *p* indexes the provider, z the ZIP code of the provider's home address, l the practice location, as identified by city, ZIP code, or address of their work location, 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 in the house price index between the end of year *t-1* and the end of year *t-2*.

Table 3 presents the results. Panel A uses the ratio of opioid prescription costs to total drug costs as the dependent variable, while Panel B uses the natural logarithm of one plus the total cost of opioids prescribed. We start with office city- or ZIP-by-year fixed effects, in addition to provider fixed effects in Columns (1) and (2), respectively.

A potential concern with our analysis is that providers' house price changes 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, *Lag Provider House Price Change* can be correlated with patients' house price changes.

To address this concern, we employ an even more stringent specification that replaces location-year fixed effects with provider office-year fixed effects in Column (3). This ap-

proach effectively compares providers working in the same office during the same year, thereby largely controlling for patient-related variables at the office-year level. The coefficient on *Lag Provider House Price Change* 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.

To further address endogeneity concerns, Column (4) 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 *Lag Provider House Price Change* remains similar to our benchmark result. The fact that the results are stable in this sample, where providers are less likely to treat their residential neighbors, provides evidence against the alternative explanation that our results merely reflect patients' economic conditions.

The estimated coefficients on *Lag Provider House Price Change* are negative and statistically significantly different from zero in all columns. The magnitudes are also economically meaningful. According to Column (3) of Panel B, when a provider's house price change drops from the 90th to the 10th percentile, she prescribes 4.3% (0.132×0.327) more opioids.

Figure 1 presents two binned scatter plots depicting the relationship between opioid prescriptions scaled by all drugs and *Lag Provider House Price Change*. Panel (a) uses the raw variables, while Panel (b) first removes provider and office ZIP-by-year fixed effects. Both plots reveal a clear negative relationship between these variables, corroborating our regression findings.

5.1 Robustness

In Table IA.1, we loosen the sample restriction by including providers who have never prescribed any opioids in our sample. The results remain similar. In Table IA.2, we use various alternative dependent variables, all measured at the provider-year level. The dependent

variables in Panel A are the ratio of total days of opioid supply relative to the total days of all drug supply in Columns (1)-(3), and the ratio of the number of opioid prescriptions relative to the number of all drug prescriptions in (4)-(6). We use three different dependent variables in Panel B. The first, *Log Opioid Days Supply*, is the natural logarithm of one plus the total number of days of opioid supply. The second, *Log Opioid Claims*, is the natural logarithm of one plus the number of opioid prescriptions. The third dependent variable, *1(Opioid>0)*, is an indicator that equals one if the provider prescribes any opioids in that year. All specifications include provider fixed effects. In addition, we include providers' office city or ZIP–year, or office-by-year fixed effects. We find that the estimated coefficients on *Lag Provider House Price Change* are negative and statistically different from zero in all columns. In other words, these alternative measures of opioid prescriptions all increase when providers' house price changes are less favorable.

Because we exclude providers who never prescribed any opioids in our main analyses, the probability of a provider prescribing opioids in a year is 94%, which means the raw amount of opioid costs is zero in only around 6% of the observations. This minimizes the econometric concerns raised by Cohn et al. (2022) regarding count data analysis. Nonetheless, we follow the suggestion by Cohn et al. (2022) and report the Poisson regression results in Table IA.3. We continue to find similar results.

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 smaller threat of patient addiction compared to their short-acting counterparts.[16] If providers' negative house price shocks only increase their prescription of long-acting opioid drugs, the negative consequences are less severe. In Table IA.4, 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 experi-

[16]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`.

encing more adverse wealth growth increase prescriptions of more addictive short-acting opioids, which pose substantial risks for patient addiction.

A potential concern is that providers experiencing worsening financial conditions may treat patients with greater clinical need for opioids, which could drive the observed increase in prescriptions. However, given that our results are robust to including both provider and office-by-year fixed effects, this concern would require that patients with higher clinical needs for opioids be disproportionately matched to providers in deteriorating financial conditions within the same office-year—an unlikely scenario. Regardless, we address this concern using provider-level patient characteristics.

Although we lack patient-level health outcomes, we observe provider-year level average Hierarchical Condition Category (HCC) risk scores for their Medicare patients. This measure predicts expected fee-for-service spending based on patient characteristics, with higher scores indicating greater expected medical service utilization and poorer health. Our analysis confirms that this average score is strongly positively correlated with providers' opioid prescriptions.

We first examine whether providers treat higher-risk patients in response to changes in house prices. In Columns (1)-(3) of Table A1, we regress providers' average patient risk scores on their lagged house price changes; the relationship is statistically insignificant. In Columns (4)-(6), we regress the logarithm of prescribed opioid costs on lagged house price changes while controlling for contemporaneous average patient risk scores. The coefficients on patient risk scores are positive and highly statistically significant, confirming that patient risk is indeed positively correlated with opioid prescriptions. Importantly, the coefficients on lagged house price changes remain comparable to those in our main results. Together, these findings offer suggestive evidence that changes in patient characteristics are unlikely to explain providers' increased opioid prescribing.

6 Provider House Price Changes Associated with Patient Visits and Charges

Having established that worse house price changes increase 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 more adverse house price changes correlate with more patient visits and charges submitted.

Table 4 Panel A examines this relationship using the same Medicare Part B data used in Table 2. Our dependent variables are the log of the number of patient visits (Columns 1-3) and the charges submitted (Columns 4-6). The key independent variable is *Lag Provider House Price Change*, measured as the lagged house price change in providers' residential ZIP codes. We maintain the same fixed effects structure: provider fixed effects throughout, with location-time controls progressing from office city-by-year to office-by-year fixed effects. The results support our prediction. The estimated coefficients on *Lag Provider House Price Change* are negative and statistically significant in all six columns.[17]

We then investigate the duration of the effect of providers' house price changes on their business volume. We hypothesize that if a provider experiences worse house price changes in year $t-1$, their actions in $t-1$ and t, such as prescribing more opioids, may continue to attract more patient visits even in $t+1$. This could be due to the spread of their reputation for catering to patient demand or the return of addicted patients seeking more opioids. To test this, we include the house price changes in $t-2$ and $t-3$ as additional independent variables in Panel B.

The results in Table 4 Panel B show negative coefficients on providers' house price changes in $t-1$, $t-2$, and $t-3$, with statistical significance for the first two. The effect is larger for house price changes in $t-2$ than in $t-1$, possibly explained by the gradual

[17] In Table IA.5, we present a version of the same table without controlling for lagged business volume. The results are highly similar.

spread of word-of-mouth and the slow accumulation of addicted patients.

To assess the overall impact of house price shocks on providers' business volume, we sum the coefficients on house price changes in $t-2$ and $t-1$, ignoring discounting. Using the estimates from Columns (3) and (6) of Table 4, a decrease in house price changes from the 90th to the 10th percentile leads to a combined 1.9% (0.102 $\times$ (0.071+0.115) and 0.102 $\times$ (0.075+0.111)) increase in the number of patient visits and total Medicare charges in the following two years. Assuming providers' compensation scales with patient visits and charge amounts, this represents a substantial increase in their earnings.

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 patient visits and charges typically translate to increased provider compensation (Reid et al., 2022), 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 Companies to Providers

Our findings indicate that providers increase their opioid prescriptions when experiencing adverse house price changes 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 A2, we estimate Equation 1 by replacing the dependent variable with an indicator 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-by-year fixed effects in Columns (1) and (3) and provider office ZIP-by-year fixed effects in (2) and (4).

The coefficients on *Lag Provider House Price Change* are negative and statistically significant across all specifications. Our estimates in Column (1) show that a decrease in house price changes from the 90th to the 10th percentile increases a provider's probability of receiving opioid-related payments by 0.4 percentage points (0.096×0.036), representing a 4% ($0.096 \times 0.036/0.086$) increase relative to the baseline probability. Similarly, Column (3) indicates that such a decline in house price changes leads to a 0.9% (0.096×0.090) increase in the amount of opioid-related payments that providers receive. While these magnitudes are modest, they provide supporting evidence for our main finding that providers' financial circumstances influence their professional behavior.

8 Effect of House 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. To exploit the historical house price shock during the Crisis, we estimate the following specification.

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

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

large house price shocks during the GFC. Note again that our prescription data start in 2010. The regression sets the last year of our sample, 2020, as the benchmark. We include provider fixed effects and office ZIP-by-year fixed effects.

Figure 2 plots the coefficients β_t and the 90% confidence intervals. The coefficients are positive and statistically significant for 2011 and 2012, with magnitudes similar to those for 2010. The estimated coefficients on the interaction term for 2010-2012 have an average of 0.007. The magnitudes suggest that providers living in ZIP codes hardest hit by the GFC increased their opioid prescriptions (scaled by all drug prescriptions) by approximately 5.8% (0.007 divided by the average of 0.12) more opioids from 2010 to 2012. The effect diminishes and becomes statistically insignificant after 2012, potentially explained by house price recoveries in previously hard-hit areas. These results suggest that financial distress can lead providers to prescribe more opioids.

Table 5 examines whether financial distress outside of the GFC is associated with increased opioid prescribing. We consider two measures. The first is an indicator for whether the provider's residential ZIP code experienced a house price change in the bottom decile of our sample during the previous year. This bottom decile corresponds to a maximum price change of -4% and a mean of -8%.

The second measure captures a more severe form of financial distress: mortgage foreclosure.[18] Following Diamond et al. (2020), who document that homeowners facing foreclosure experience financial distress over two to three years, we define this indicator as whether the provider experienced mortgage foreclosure between years $t-2$ and t. We include year t because providers undergoing foreclosure at any point during the year likely feel financial pressure from the beginning of that year and, thus, may change their prescription decisions throughout the year.

We estimate specifications with provider fixed effects and either office city-by-year or ZIP-by-year fixed effects. Columns (1)-(4) use the ratio of opioid costs to total prescription

[18]Table IA.6 suggests that providers experiencing worse lagged house price changes are more likely to undergo mortgage foreclosure.

costs as the dependent variable, while Columns (5)-(8) use the natural log of opioid costs.

The estimated coefficients on both financial distress indicators are positive across all specifications and statistically significant in five columns. Based on Column (2), providers experiencing bottom-decile house price changes prescribe 2.4% (0.003/0.123) more opioids relative to the mean. Based on Column (4), providers experiencing mortgage foreclosure prescribe 5.5% (0.007/0.127) more opioids relative to the mean. These results suggest that providers experiencing financial distress prescribe more opioids, reinforcing our main findings.

9 Stronger Effects among Providers with Lower Income

If financial considerations drive providers' opioid prescribing behavior, the effects should be stronger among providers with lower labor income and, thus, have more of their net worth concentrated in housing. To test this hypothesis, we match providers to occupation-location-level income data from the BLS for the previous year. Due to coverage limitations in the BLS data, only a subsample of providers is matched.

In Columns (1), (2), (5), and (6) of Table 6, we augment our main specification with an interaction term between lagged house price changes and lagged labor income. We standardize income to have a median of zero and a standard deviation of one, so that the coefficient on lagged house price changes represents the effect for providers at the median income level.

A potential concern is that higher incomes may simply compensate for higher costs of living, in which case providers across income levels may not respond differentially to house price shocks. To address this, we match providers to lagged Regional Price Parities from the Bureau of Economic Analysis. In Columns (3), (4), (7), and (8), we include an interaction between lagged house price changes and this cost-of-living measure, which is similarly standardized at the median. This allows us to separate the role of income from

geographic cost-of-living differences.

The coefficients on the interaction between lagged house price changes and provider income are positive and statistically significant across all columns, indicating that lower-income providers respond more strongly to declines in house prices. In Column (8), the coefficient on lagged house price changes at the median income level is -0.663. For providers with income one standard deviation below the median, the total effect is -1.544 ($-0.663-0.881$), approximately 2.3 times as large. These results provide additional support for the hypothesis that providers increase opioid prescriptions when their financial conditions deteriorate.

10 Stronger Effects among Providers Serving Vulnerable Patients

The increased opioid prescriptions resulting from providers' adverse wealth shocks would be particularly concerning if they disproportionately affect vulnerable patient populations who face higher risks of addiction. Prior research has established that individuals with lower incomes face elevated risks of opioid addiction and overdose deaths.[19] We next examine whether providers practicing in lower-income ZIP codes respond more strongly to their own financial conditions, using lagged median income at the office ZIP code level based on ACS data.

In Columns (1) and (2) of Table 7, we add to our main specification from Column (1) of Table 3 an interaction term between providers' lagged house price changes and lagged ZIP-level median log income, the latter of which is standardized to have a median of zero and a standard deviation of one. The dependent variable is the ratio of opioid to total prescription costs in Column (1) and the logarithm of opioid prescriptions in Column (2).

[19] See Altekruse et al. (2020), Friedman et al. (2019), Nestvold et al. (2023), and Office of the Assistant Secretary for Planning and Evaluation (2018).

The coefficients on the interaction terms are positive and statistically significant, indicating that providers practicing in lower-income ZIP codes respond more strongly to changes in house prices. According to Column (2), providers working in ZIP codes with median income one standard deviation below the sample median are 79% (0.350/0.441) more responsive to house price changes in their opioid prescribing.

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 for minority patients. While we lack patient-level data, Medicare Part D provides the demographic composition of each provider's beneficiaries. We calculate the share of each provider's patients who are non-white.

In Columns (3)-(4), we include interaction terms between providers' lagged house price changes and their non-white patient share, the latter of which is similarly standardized to the median. The estimated coefficients on the interaction term are negative and statistically significant in both columns. According to Column (4), providers with a non-white patient share one standard deviation above the median are three times (0.360/0.120) more responsive to their house price changes in their opioid prescribing, compared to those at the median. The results in this section suggest that providers experiencing adverse house price changes increase opioid prescriptions more when their patient population is more vulnerable to opioid addiction.

11 Policy Intervention Weakens Effects

To address opioid overprescribing, states introduced Prescription Drug Monitoring Programs (PDMPs), which track patients' current and past use of controlled substances. Initially, providers could access these databases voluntarily, but participation was low. As a result, between 2012 and 2019, 33 states adopted must-access mandates, requiring

providers to review prescription histories before prescribing opioids. Studies argue that these laws reduced opioid prescriptions (Wen et al., 2019).

We hypothesize that the effect of providers' financial conditions on prescribing behavior diminishes following the implementation of PDMPs. To test this, we examine how providers' house price changes influence their opioid prescribing patterns before and after policy adoption. We employ a stacked difference-in-differences approach (Gormley and Matsa, 2011), using the ratio of opioid to total prescription costs as the dependent variable.[20] We define the event year as the year a state first adopted a PDMP, following the timing in Finkelstein et al. (2025). Figure A1 plots the coefficients for each year from three years before to three years after the event year, controlling for provider fixed effects and office ZIP-by-year fixed effects. The estimates indicate that the effect is concentrated in the pre-policy period and becomes economically small and statistically insignificant after policy adoption. These findings provide suggestive evidence that state opioid regulations reduced the influence of providers' financial pressures on their prescribing decisions.

12 Provider Financial Conditions Affect ADHD Drug Prescriptions

In this section, we extend our analysis of opioid prescription to drugs used to treat ADHD. Recent reports have uncovered the abuse of ADHD drug prescriptions.[21] Since such drugs have gained more attention among potential recipients since 2013 (Zhao et al., 2022), we focus on the sample period of 2013 and later. For the analyses in this section, we exclude providers who never prescribed ADHD medications between 2013 and 2020.

Table 8 repeats our main analysis on opioid prescription, replacing the dependent vari-

[20] Baker et al. (2022) recommend the stacked difference-in-differences approach as one of three preferred methods in staggered adoption settings.

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

able with the provider-year level share of ADHD drug costs relative to total prescribed drug costs (Columns 1 to 3) and total ADHD drug costs in natural logs (Columns 4 to 6). Based on Column (6), where we control for provider fixed effects and office-by-year fixed effects, when providers experience a decline in house price changes from the 90th to the 10th percentile (9.2 percentage points), they prescribe 9% (0.092×0.982) more ADHD drugs. 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 our results.

13 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 the potential for misuse. 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. When a provider's house price change drops from the 90th to the 10th percentile, she prescribes 4.3% more opioids.

Consistent with our baseline result, providers living in ZIP codes with bottom-half price changes during 2007-2009 increased their opioid prescriptions by 5.8% more in 2010-2012, compared to other providers working in the same ZIP codes. In addition, providers with lower labor-income levels respond approximately 2.3 times more strongly than median-income providers.

In addition, we find that providers practicing in low-income ZIP codes and those with higher proportions of non-white patients exhibit substantially larger increases in opioid prescriptions when experiencing worse house price changes. These results suggest that providers are potentially less responsible in their opioid prescriptions for patients who are already more 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 prescription drug monitoring programs reduced the influence of providers' 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.

Finally, we extend our analysis to ADHD medications, which also have significant potential for misuse and documented concerns about inappropriate prescribing. We find that providers similarly increase ADHD prescriptions when experiencing a more adverse house price change. This parallel pattern suggests that the influence of providers' financial circumstances on prescribing behavior extends beyond opioids to other medications with overprescription potential, underscoring broader implications for medical decision-making.

Our results carry important implications. For healthcare policy, they suggest that moving providers away from volume-based compensation may reduce the overprescription of addictive medications and unnecessary medical services. More broadly, our findings reveal that economic stress can compromise professional decision-making in settings with conflicts of interest—a concern that potentially extends to finance, law, consulting, and other fields. Employers and regulators should consider heightened monitoring of professional conduct during economic downturns, when financial stress may simultaneously affect decision-making across entire sectors or regions.

References

Adelino, M., K. Lewellen, and W. B. McCartney (2022). Hospital financial health and clinical choices: evidence from the financial crisis. *Management Science 68*(3), 2098–2119.

Adelino, M., K. Lewellen, and A. Sundaram (2015). Investment decisions of nonprofit firms: Evidence from hospitals. *The Journal of Finance 70*(4), 1583–1628.

Agarwal, S. (2007). The impact of homeowners' housing wealth misestimation on consumption and saving decisions. *Real Estate Economics 35*(2), 135–154.

Agha, L. and D. Zeltzer (2022). Drug diffusion through peer networks: The influence of industry payments. *American Economic Journal: Economic Policy 14*(2), 1–33.

Aghamolla, C., J. Jain, and R. T. Thakor (2023). When private equity comes to town: The local economic consequences of rising healthcare costs. *Available at SSRN*.

Aghamolla, C., P. Karaca-Mandic, X. Li, and R. T. Thakor (2024). Merchants of death: The effect of credit supply shocks on hospital outcomes. *American Economic Review 114*(11), 3623–3668.

Al-Sabah, T. and P. Ouimet (2021). For better or worse? the economic implications of paid sick leave mandates. *The Economic Implications of Paid Sick Leave Mandates (October 30, 2021). Kenan Institute of Private Enterprise Research Paper* (3953523).

Aladangady, A. (2017). Housing wealth and consumption: Evidence from geographically linked microdata. *American Economic Review*, 3415–3446.

Alexander, D. and M. Schnell (2024). The impacts of physician payments on patient access, use, and health. *American Economic Journal: Applied Economics 16*(3), 142–177.

Altekruse, S. F., C. M. Cosgrove, W. C. Altekruse, R. A. Jenkins, and C. Blanco (2020). Socioeconomic risk factors for fatal opioid overdoses in the united states: Findings from the mortality disparities in american communities study (mdac). *PLoS One 15*(1), e0227966.

Aslan, H. (2022). Personal financial distress, limited attention. *Journal of Accounting Research 60*(1), 97–128.

Baker, A. C., D. F. Larcker, and C. C. Wang (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics 144*(2), 370–395.

Barnett, M. L. and E. Meara (2023). Racial inequality in receipt of medications for opioid use disorder. *New England Journal of Medicine 388*(19), 1755–1764.

Batty, M. and B. Ippolito (2017). Financial incentives, hospital care, and health outcomes: evidence from fair pricing laws. *American Economic Journal: Economic Policy 9*(2), 28–56.

Berger, D., V. Guerrieri, G. Lorenzoni, and J. Vavra (2017). House prices and consumer spending. *Review of Economic Studies 85*, 1502–1542.

Bernstein, A. (2021). Negative home equity and household labor supply. *Journal of Finance 76*, 2963–2995.

Bernstein, S., T. McQuade, and R. R. Townsend (2021). Do household wealth shocks affect productivity? evidence from innovative workers during the great recession. *The Journal of Finance 76*(1), 57–111.

Brown, J. and D. A. Matsa (2020). Locked in by leverage: Job search during the housing crisis. *Journal of Financial Economics 136*(3), 623–648.

Campbell, J. Y. and J. F. Cocco (2007). How do house prices affect consumption? evidence from micro data. *Journal of monetary Economics 54*(3), 591–621.

Carey, C., E. M. Lieber, and S. Miller (2021). Drug firms' payments and physicians' prescribing behavior in medicare part d. *Journal of Public Economics 197*, 104402.

Carrico, J. A., K. Mahoney, K. M. Raymond, L. Mims, P. C. Smith, J. T. Sakai, S. K. Mikulich-Gilbertson, C. J. Hopfer, and K. Bartels (2018). The impact of patient satisfaction scores on opioid prescribing. *Journal of the American Board of Family Medicine 31*(4), 517–525.

Carvalho, D., J. Gao, and P. Ma (2023). Loan spreads and credit cycles: The role of lenders' personal economic experiences. *Journal of Financial Economics 148*(2), 118–149.

Centers for Medicare & Medicaid Services (2017, January 5). Opioid misuse strategy. Technical report, Centers for Medicare & Medicaid Services.

Cher, B. A., N. E. Morden, and E. Meara (2019). Medicaid expansion and prescription trends: opioids, addiction therapies, and other drugs. *Medical care 57*(3), 208–212.

Clemens, J. and J. D. Gottlieb (2014). Do physicians' financial incentives affect medical treatment and patient health? *American Economic Review 104*(4), 1320–1349.

Clifford, C. P., J. A. Ellis, and W. C. Gerken (2025). Childhood exposure to misbehavior and the culture of financial misconduct. *The Review of Financial Studies*, hhaf075.

Cohn, J. B., Z. Liu, and M. I. Wardlaw (2022). Count (and count-like) data in finance. *Journal of Financial Economics 146*(2), 529–551.

Cornaggia, K., J. Hund, G. Nguyen, and Z. Ye (2022). Opioid crisis effects on municipal finance. *The Review of Financial Studies 35*(4), 2019–2066.

Cornaggia, K., J. Hund, K. Pisciotta, and Z. Ye (2023). Spillover effects of opioid abuse on skilled human capital and innovation activity. *Available at SSRN 4104835*.

Cornaggia, K., X. Li, and Z. Ye (2024). Financial effects of remote product delivery: Evidence from hospitals. *The Review of Financial Studies 37*(9), 2817–2854.

Cornaggia, K., X. Li, and Z. Ye (2025). Hedging or healing: How business cycle exposure affects the safety net. Available at SSRN: https://ssrn.com/abstract=5677662.

Currie, J., A. Li, and M. Schnell (2023). The effects of competition on physician prescribing. Technical report, National Bureau of Economic Research.

Dasgupta, N., L. Beletsky, and D. Ciccarone (2018). Opioid crisis: No easy fix to its social and economic determinants. *American Journal of Public Health 108*(2), 182–186.

Diamond, R., A. Guren, and R. Tan (2020). The effect of foreclosures on homeowners, tenants, and landlords. Technical report, National Bureau of Economic Research.

Dimmock, S. G., J. A. Ellis, and W. C. Gerken (2025). Death of a salesman's manager: Conflicted supervision and the dark side of soft information. *Available at SSRN 5025434*.

Dimmock, S. G. and W. C. Gerken (2012). Predicting fraud by investment managers. *Journal of Financial Economics 105*(1), 153–173.

Dimmock, S. G., W. C. Gerken, and T. V. Alfen (2021). Real estate shocks and financial advisor misconduct. *Journal of Finance 76*, 3309–3346.

Dimmock, S. G., W. C. Gerken, and N. P. Graham (2018). Is fraud contagious? coworker influence on misconduct by financial advisors. *The Journal of Finance 73*(3), 1417–1450.

Dranove, D., C. Garthwaite, and C. Ody (2017). How do nonprofits respond to negative wealth shocks? the impact of the 2008 stock market collapse on hospitals. *The RAND Journal of Economics 48*(2), 485–525.

Egan, M. (2019). Brokers versus retail investors: Conflicting interests and dominated products. *The Journal of Finance 74*(3), 1217–1260.

Egan, M., S. Ge, and J. Tang (2022). Conflicting interests and the effect of fiduciary duty: Evidence from variable annuities. *The Review of Financial Studies 35*(12), 5334–5386.

Egan, M., G. Matvos, and A. Seru (2019). The market for financial adviser misconduct. *Journal of Political Economy 127*(1), 233–295.

Einav, L., A. Finkelstein, and N. Mahoney (2018). Provider incentives and healthcare costs: Evidence from long-term care hospitals. *Econometrica 86*(6), 2161–2219.

Finkelstein, A., M. Gentzkow, and D. Li (2025). What drives risky prescription opioid use? evidence from migration. *The quarterly journal of economics 140*(4), 3133–3189.

Fleischman, W., S. Agrawal, C. P. Gross, and J. S. Ross (2019). Association of pharmaceutical manufacturer payments to physicians and prescribing dosage of opioids. *Journal of General Internal Medicine 34*, 1074–1076.

Florence, C., F. Luo, and K. Rice (2021). The economic burden of opioid use disorder and fatal opioid overdose in the united states, 2017. *Drug and Alcohol Dependence 218*, 108350.

Frenk, S. M., K. S. Porter, and L. Paulozzi (2015). Prescription opioid analgesic use among adults: United states, 1999-2012. Technical Report 2015, US Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Health Statistics.

Friedman, J., D. Kim, T. Schneberk, P. Bourgois, M. Shin, A. Celious, and D. L. Schriger (2019). Assessment of racial/ethnic and income disparities in the prescription of opioids and other controlled medications in california. *JAMA Internal Medicine 179*(4), 469–476.

Gallagher, E. A., R. Gopalan, and M. Grinstein-Weiss (2019). The effect of health insurance on home payment delinquency: Evidence from aca marketplace subsidies. *Journal of Public Economics 172*, 67–83.

Gao, J., S. Ge, L. Schmidt, and C. Tello-Trillo (2022). How do health insurance costs affect low-and high-income workers? *NYU Stern Working Paper*.

Gao, J., Y. Kim, and M. Sevilir (2025). Private equity in the hospital industry. *Journal of Financial Economics 171*, 104107.

Gao, J., T. Liu, S. Malik, and M. Sevilir (2024). Can nonprofits save lives under financial stress? evidence from the hospital industry. *Available at SSRN 4946064*.

Gomes, T., M. Tadrous, M. M. Mamdani, J. M. Paterson, and D. N. Juurlink (2018). The burden of opioid-related mortality in the united states. *JAMA Network Open 1*(2), e180217.

Gormley, T. A. and D. A. Matsa (2011). Growing out of trouble? corporate responses to liability risk. *The Review of Financial Studies 24*(8), 2781–2821.

Griffin, J. M. and A. Priest (2024). Overbilling and killing? an examination of the skilled nursing industry. *An Examination of the Skilled Nursing Industry (October 15, 2024)*.

Gruber, J. and M. Owings (1994). Physician financial incentives and cesarean section delivery.

Gupta, A., S. T. Howell, C. Yannelis, and A. Gupta (2024). Owner incentives and performance in healthcare: private equity investment in nursing homes. *The Review of Financial Studies 37*(4), 1029–1077.

Hackmann, M. B., R. V. Pohl, and N. R. Ziebarth (2024). Patient versus provider incentives in long-term care. *American Economic Journal: Applied Economics 16*(3), 178–218.

Hadland, S. E., M. Cerdá, Y. Li, M. S. Krieger, and B. D. Marshall (2018). Association of pharmaceutical industry marketing of opioid products to physicians with subsequent opioid prescribing. *JAMA internal medicine 178*(6), 861–863.

Hadland, S. E., A. Rivera-Aguirre, B. D. Marshall, and M. Cerdá (2019). Association of pharmaceutical industry marketing of opioid products with mortality from opioid-related overdoses. *JAMA Network Open 2*(1), e186007–e186007.

Hollander, M. A., J. M. Donohue, B. D. Stein, E. E. Krans, and M. P. Jarlenski (2020). Association between opioid prescribing in medicare and pharmaceutical company gifts by physician specialty. *Journal of general internal medicine 35*, 2451–2458.

Howell, S. T. and T. Liu (2023). *Private Equity in Healthcare*. Cham: Palgrave Macmillan.

Inoue, K., J. F. Figueroa, E. J. Orav, and Y. Tsugawa (2020). Association between industry payments for opioid products and physicians' prescription of opioids: observational study with propensity-score matching. *J Epidemiol Community Health 74*(8), 647–654.

Jacobson, M., T. Y. Chang, J. P. Newhouse, C. C. Earle, et al. (2013). Physician agency and competition: Evidence from a major change to medicare chemotherapy reimbursement policy. Technical report, National Bureau of Economic Research.

Jacobson, M., C. C. Earle, M. Price, and J. P. Newhouse (2010). How medicare's payment cuts for cancer chemotherapy drugs changed patterns of treatment. *Health Affairs 29*(7), 1391–1399.

Jacobson, M., A. J. O'Malley, C. C. Earle, J. Pakes, P. Gaccione, and J. P. Newhouse (2006). Does reimbursement influence chemotherapy treatment for cancer patients? *Health Affairs 25*(2), 437–443.

Kolodny, A., D. T. Courtwright, C. S. Hwang, P. Kreiner, J. L. Eadie, T. W. Clark, and G. C. Alexander (2015). The prescription opioid and heroin crisis: A public health approach to an epidemic of addiction. *Annual Review of Public Health 36*, 559–574.

Lee, A. J., J. Bandari, L. C. Macleod, B. J. Davies, and B. L. Jacobs (2019). Concentration of opioid-related industry payments in opioid crisis areas. *Journal of General Internal Medicine 34*, 187–189.

Li, X. and T. J. Tong (2025, March). Retention costs or human capital investments: A dual perspective on employer-sponsored health benefits. Available at SSRN: `https://ssrn.com/abstract=5429635`.

Li, X. and Z. Ye (2022). Propagation of the opioid epidemic in the banking sector. *Available at SSRN 4148134*.

Liu, T. (2022). Bargaining with private equity: Implications for hospital prices and patient welfare. *Available at SSRN 3896410*.

Maclean, J. C., J. Mallatt, C. J. Ruhm, and K. Simon (2020). Economic studies on the opioid crisis: A review.

Mason, M., R. Soliman, H. S. Kim, and L. A. Post (2022). Disparities by sex and race and ethnicity in death rates due to opioid overdose among adults 55 years or older, 1999 to 2019. *JAMA network open 5*(1), e2142982–e2142982.

Matsa, D. A. (2007). Does malpractice liability keep the doctor away? evidence from tort reform damage caps. *The Journal of Legal Studies 36*(S2), S143–S182.

Maturana, G. and J. Nickerson (2020). Real effects of workers' financial distress: Evidence from teacher spillovers. *Journal of Financial Economics 136*(1), 137–151.

Meinhofer, A. and A. E. Witman (2018). The role of health insurance on treatment for opioid use disorders: Evidence from the affordable care act medicaid expansion. *Journal of health economics 60*, 177–197.

Mojtabai, R. (2017). National trends in long-term use of prescription opioids. *Pharmacoepidemiology and Drug Safety*.

Mullainathan, S., M. Noeth, and A. Schoar (2012). The market for financial advice: An audit study. Technical report, National Bureau of Economic Research.

Nestvold, H. H., S. S. Skurtveit, A. Hamina, V. Hjellvik, and I. Odsbu (2023). Socioeconomic risk factors for long-term opioid use: A national registry-linkage study. *European Journal of Pain*.

Newham, M. and M. Valente (2024). The cost of influence: how gifts to physicians shape prescriptions and drug costs. *Journal of Health Economics 95*, 102887.

Nguyen, T. D., W. D. Bradford, and K. I. Simon (2019). Pharmaceutical payments to physicians may increase prescribing for opioids. *Addiction 114*(6), 1051–1059.

Office of the Assistant Secretary for Planning and Evaluation (2018). The opioid crisis and economic opportunity: Geographic and economic trends. Aspe research brief, U.S. Department of Health and Human Services.

Ouimet, P., E. Simintzi, and K. Ye (2023). The impact of the opioid crisis on firm value and investment. *Available at SSRN 3338083*.

Pool, V. K., N. Stoffman, S. E. Yonker, and H. Zhang (2019). Do shocks to personal wealth affect risk-taking in delegated portfolios? *The Review of Financial Studies 32*(4), 1457–1493.

Reid, R. O., A. K. Tom, R. M. Ross, E. L. Duffy, and C. L. Damberg (2022, January). Physician compensation arrangements and financial performance incentives in us health systems. *JAMA Health Forum 3*(1), e214634.

Schneider, B. J., R. Ehsanian, D. J. Kennedy, A. Schmidt, L. Huynh, and D. P. Maher (2022). The effect of patient satisfaction scores on physician clinical decision making: a possible factor driving utilization of opioid prescriptions, magnetic resonance imaging, and interventional spine procedures. *Interventional Pain Medicine 1*(1), 100012.

Sites, B. D., J. Harrison, M. D. Herrick, M. M. Masaracchia, M. L. Beach, and M. A. Davis (2018). Prescription opioid use and satisfaction with care among adults with musculoskeletal conditions. *The Annals of Family Medicine 16*(1), 6–13.

Stroebel, J. and J. Vavra (2019). House prices, local demand, and retail prices. *Journal of Political Economy 127*(3), 1391–1436.

Tilly, J., S. Skowronski, and S. Ruiz (2017, December). The opioid public health emergency and older adults. Technical report, Administration for Community Living.

Tong, J. T. (2021). Health care costs and corporate investment. *Working Paper*.

Vogel, L. (2019). Pharma freebies for doctors linked to opioid prescribing habits.

Wang, Y. (2025). Does physicians' financial health affect medical treatment and patient outcomes? Available at: https://www.yanhaowang.com/files/paper/Physician%20Financial%20Health_Yanhao%20Wang_July%202025.pdf.

Wen, H., J. M. Hockenberry, P. J. Jeng, and Y. Bao (2019). Prescription drug monitoring program mandates: impact on opioid prescribing and related hospital use. *Health Affairs 38*(9), 1550–1556.

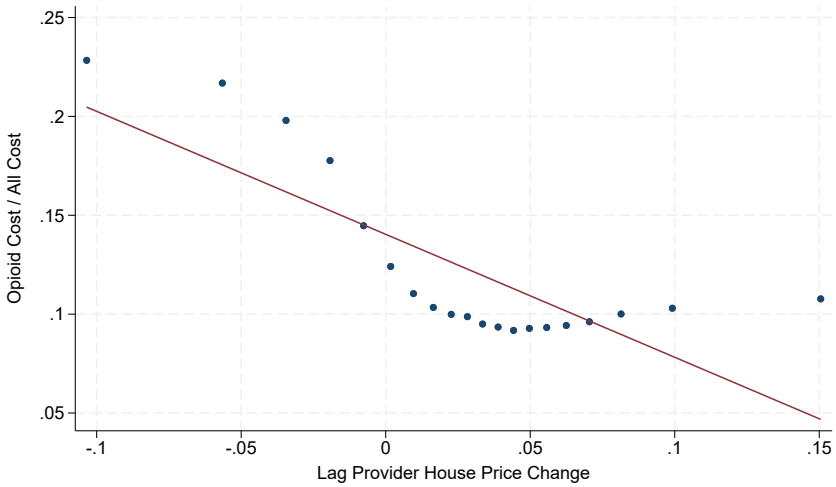
Yip, W. C. (1998). Physician response to medicare fee reductions: changes in the volume of coronary artery bypass graft (cabg) surgeries in the medicare and private sectors. *Journal of health economics 17*(6), 675–699.

Zezza, M. A. and M. A. Bachhuber (2018). Payments from drug companies to physicians are associated with higher volume and more expensive opioid analgesic prescribing. *PLoS One 13*(12), e0209383.

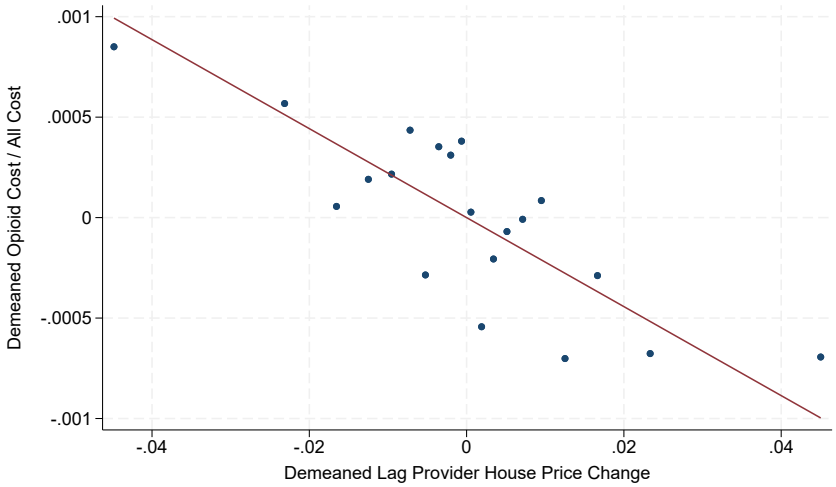
Zhao, X., S. J. Coxe, A. C. Timmons, and S. L. Frazier (2022). Mental health information seeking online: a google trends analysis of adhd. *Administration and Policy in Mental Health and Mental Health Services Research*, 1–17.

Figure 1: Opioid Prescriptions vs Provider House Price Change

(a) Using Raw Variables

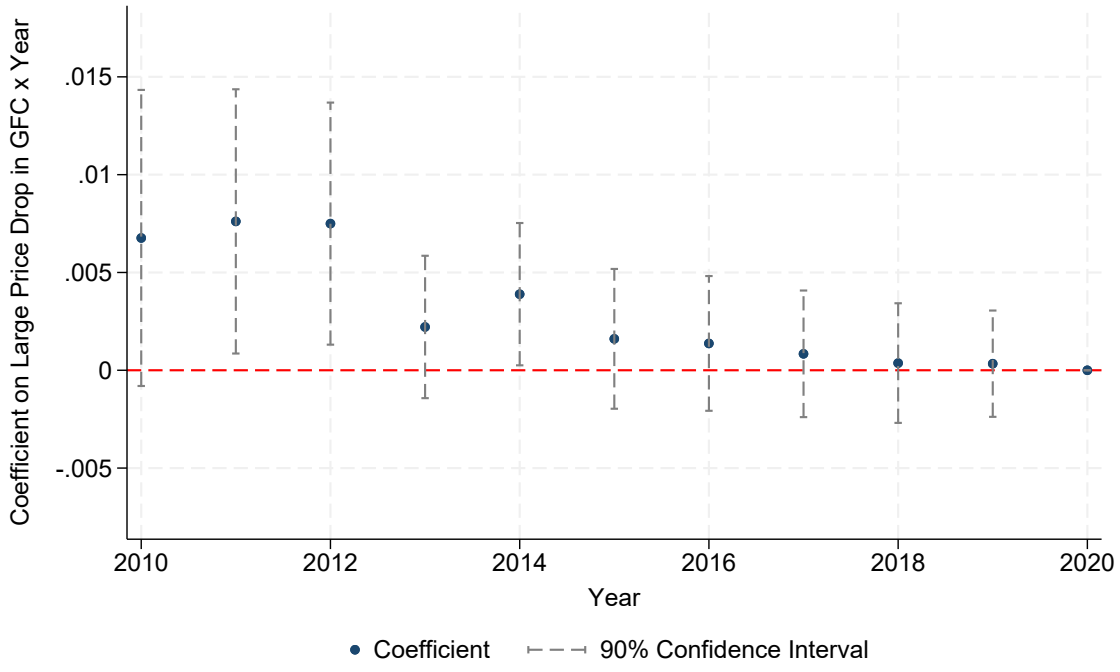


(b) Using Demeaned Variables



These figures present binscatter plots depicting the relation between healthcare providers' financial conditions and the amount of opioids they prescribe. The x-axis indicates *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 *Opioid Cost/All Cost*, which is the cost of opioids prescribed by a provider divided by the cost of all drugs prescribed by the same provider. 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:

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

The dependent variable is the cost of opioids prescribed by provider p divided by the cost of all drugs prescribed by the same provider in year t. *1(Large Price Drop in GFC)* indicates providers living in ZIP codes that experienced house price 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
Lag Provider House Price Change	0.03	0.06	-0.00	0.03	0.06
Opioid Cost	6,236.93	16,646.91	171.18	651.48	3,869.04
Opioid Days Supply	3,339.99	6,942.40	139.00	601.00	3,100.00
Opioid Claims	154.90	270.76	21.00	53.85	157.00
Log Opioid Cost	6.48	2.58	5.15	6.48	8.26
Log Opioid Days Supply	6.25	2.45	4.94	6.40	8.04
Log Opioid Claims	4.00	1.62	3.09	4.00	5.06
Opioid Cost/All Cost	0.12	0.21	0.01	0.03	0.13
Opioid Days Supply/All Days Supply	0.11	0.19	0.01	0.03	0.12
Opioid Claims/All Claims	0.18	0.22	0.03	0.07	0.25
Distance between Home and Office	12.55	10.62	4.41	9.45	18.01
Provider Income	116,752.35	33,237.17	94,910.00	107,850.00	135,640.00
Cost of Living (RPP)	100.92	7.42	95.15	99.58	105.86
Office ZIP Median Log Income	60,372.55	25,550.79	42,434.00	54,591.00	73,162.00
Provider Non-White Patient Share	0.23	0.24	0.07	0.16	0.32

This table presents summary statistics of the variables used in our estimations. *Lag Provider House Price Change* is the annual house price growth rate in the provider's residential ZIP code, 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, or Claims* is (the natural logarithm of one plus) the cost, the number of days supplied, or the number of claims of opioids prescribed by the provider. *Opioid Cost/All Cost* is the opioid cost divided by the cost of all drugs prescribed by the provider. *Opioid Days Supply/All Days Supply* is the total number of days' supply for opioid prescriptions divided by the total days' supply for all drugs prescribed by the provider. *Opioid Claims/All Claims* is the number of opioid prescription claims divided by the total number of prescription claims for all drugs prescribed by the provider.

Table 2: Relationship between Provider Lagged Opioid Prescriptions and Patient Visits or Charges

Panel A: Last Year Opioid Prescription Scaled by All Drugs

	Log # Patient Visits			Log Submitted Charges		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Opioid Cost/All Cost	0.052***	0.051***	0.013	0.053***	0.051***	0.008
	(5.00)	(4.90)	(1.05)	(4.73)	(4.55)	(0.60)
Lag Log # Patient Visits	0.341***	0.332***	0.308***			
	(111.09)	(107.89)	(69.39)			
Lag Log Submitted Charges				0.362***	0.352***	0.322***
				(123.97)	(119.49)	(73.85)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	5.949	5.952	5.985	11.038	11.041	11.125
Y SD	1.067	1.066	1.028	1.139	1.138	1.080
X Mean	0.067	0.068	0.075	0.067	0.068	0.075
X SD	0.148	0.148	0.154	0.148	0.148	0.154
X 90Pct - 10Pct	0.217	0.218	0.256	0.217	0.218	0.256
N	646,102	639,882	399,625	646,102	639,882	399,625

Panel B: Last Year Opioid Prescriptions

	Log # Patient Visits			Log Submitted Charges		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Log Opioid Cost	0.008***	0.008***	0.007***	0.007***	0.007***	0.006***
	(8.43)	(7.86)	(5.01)	(6.97)	(6.37)	(4.22)
Lag Log # Patient Visits	0.339***	0.330***	0.306***			
	(109.61)	(106.48)	(68.35)			
Lag Log Submitted Charges				0.360***	0.351***	0.320***
				(122.81)	(118.42)	(72.94)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	5.949	5.952	5.985	11.038	11.041	11.125
Y SD	1.067	1.066	1.028	1.139	1.138	1.080
X Mean	5.854	5.857	6.106	5.854	5.857	6.106
X SD	3.521	3.520	3.343	3.521	3.520	3.343
X 90Pct - 10Pct	9.783	9.784	9.745	9.783	9.784	9.745
N	646,102	639,882	399,625	646,102	639,882	399,625

This table examines how providers' services delivered and charges submitted are related to their opioid prescriptions in the previous year. The dependent variable is the log number of patient visits in Columns (1)-(3) and the log amount of charges submitted in Columns (4)-(6). The independent variable is providers' opioid prescription in the previous year, measured as the ratio of opioid prescription cost to all drug cost in Panel A and log opioid prescription in dollar cost in Panel B. We control for provider fixed effects in all specifications. In addition, we include office city–year fixed effects, office ZIP–year fixed effects, and office–year fixed effects by steps, 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 clustered at the provider level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

Table 3: Effect of Provider House Price Changes on Opioid Prescriptions

Panel A: Opioid Prescription Scaled by All Drugs

	Opioid Cost/All Cost			
	(1)	(2)	(3)	(4)
Lag Provider House Price Change	-0.022***	-0.022***	-0.024***	-0.022**
	(-3.50)	(-3.58)	(-2.97)	(-2.56)
Sample Restriction				Home Far to Office
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y			
Office Zip × Year FE		Y		Y
Office × Year FE			Y	
Y Mean	0.123	0.123	0.124	0.126
Y SD	0.212	0.212	0.217	0.216
X Mean	0.027	0.027	0.028	0.028
X SD	0.056	0.056	0.055	0.055
X 90Pct - 10Pct	0.132	0.132	0.132	0.131
N	1,615,442	1,606,410	1,078,698	773,651

Panel B: Log Opioid Prescriptions

	Log Opioid Cost			
	(1)	(2)	(3)	(4)
Lag Provider House Price Change	-0.448***	-0.349***	-0.327***	-0.282***
	(-6.52)	(-5.08)	(-3.89)	(-3.03)
Sample Restriction				Home Far to Office
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y			
Office Zip × Year FE		Y		Y
Office × Year FE			Y	
Y Mean	6.482	6.485	6.648	6.385
Y SD	2.582	2.580	2.465	2.569
X Mean	0.027	0.027	0.028	0.028
X SD	0.056	0.056	0.055	0.055
X 90Pct - 10Pct	0.132	0.132	0.132	0.131
N	1,615,442	1,606,410	1,078,698	773,651

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 Panel A, the dependent variable is *Opioid Cost/All Cost*, the ratio of opioid prescription relative to total drug prescription in terms of total costs. In Panel B, the dependent variable is *Log Opioid Cost*, the natural logarithm of one plus the cost of opioids prescribed. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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, in both panels, Columns (1) includes providers' office city–year fixed effects. Column (2) includes providers' office ZIP–year fixed effects. Column (3) includes providers' office–year fixed effects with *Office* referring to the provider's office Placekey ID, the identifier for a physical place. Column (4) uses a subsample of providers with distances between home and offices that are greater than the sample median. *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 of Provider House Price Changes on Patient Visits and Charges

Panel A: House Price Change of the Last Year

	Log # Patient Visits			Log Submitted Charges		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.066***	-0.059**	-0.058*	-0.060**	-0.057**	-0.063*
	(-2.60)	(-2.29)	(-1.72)	(-2.22)	(-2.08)	(-1.75)
Lag Log # Patient Visits	0.340***	0.335***	0.308***			
	(138.10)	(135.96)	(89.21)			
Lag Log Submitted Charges				0.359***	0.353***	0.320***
				(151.86)	(148.47)	(94.03)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	5.868	5.871	5.894	10.964	10.967	11.036
Y SD	1.094	1.094	1.069	1.160	1.160	1.121
X Mean	0.046	0.046	0.045	0.046	0.046	0.045
X SD	0.040	0.040	0.039	0.040	0.040	0.039
X 90Pct - 10Pct	0.090	0.090	0.089	0.090	0.090	0.089
N	860,988	854,993	568,234	860,988	854,993	568,234

Panel B: House Price Changes of the Last Three Years

	Log # Patient Visits			Log Submitted Charges		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.049*	-0.055*	-0.071*	-0.039	-0.047	-0.075*
	(-1.69)	(-1.87)	(-1.76)	(-1.24)	(-1.49)	(-1.76)
Lag2 Provider House Price Change	-0.101***	-0.084***	-0.115***	-0.095***	-0.072**	-0.111***
	(-3.58)	(-2.94)	(-2.97)	(-3.13)	(-2.35)	(-2.69)
Lag3 Provider House Price Change	-0.039	-0.017	-0.028	-0.037	-0.020	-0.019
	(-1.46)	(-0.61)	(-0.77)	(-1.32)	(-0.68)	(-0.50)
Lag Log # Patient Visits	0.366***	0.359***	0.324***			
	(113.80)	(110.78)	(69.60)			
Lag Log Submitted Charges				0.378***	0.370***	0.331***
				(124.34)	(120.63)	(73.28)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	5.911	5.913	5.935	11.023	11.026	11.097
Y SD	1.077	1.076	1.051	1.145	1.144	1.104
X Mean	0.045	0.045	0.045	0.045	0.045	0.045
X SD	0.044	0.044	0.044	0.044	0.044	0.044
X 90Pct - 10Pct	0.102	0.102	0.102	0.102	0.102	0.102
N	653,401	648,301	420,650	653,401	648,301	420,650

This table examines the relationship using the same Medicare Part B data employed in Table 2. The dependent variables are the log number of patient visits (Columns 1-3) and charges submitted (Columns 4-6). The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the previous year. Panel B further includes the house price growth rate in the provider's residential ZIP code during the previous two and three years. We maintain provider fixed effects throughout, with location controls progressing from office city–year to office ZIP–year then to office–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: Effect of Bottom Decile House Price Change and Foreclosure on Opioid Prescriptions

	Opioid Cost / All Cost				Log Opioid Cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Lag Provider House Price Change $\leq$ -4%)	0.003***	0.003***			0.012	0.006		
(bottom decile)	(2.79)	(3.02)			(1.47)	(0.68)		
Provider Mortgage Foreclosure			0.007**	0.007**			0.046	0.061*
			(2.03)	(2.29)			(1.34)	(1.80)
Provider FE	Y	Y	Y	Y	Y	Y	Y	Y
Office City $\times$ Year FE	Y		Y		Y		Y	
Office Zip $\times$ Year FE		Y		Y		Y		Y
Y Mean	0.123	0.123	0.127	0.127	6.482	6.485	6.447	6.452
Y SD	0.212	0.212	0.217	0.217	2.582	2.580	2.539	2.536
X Mean	0.109	0.108	0.007	0.007	0.109	0.108	0.007	0.007
N	1,615,442	1,606,410	893,018	883,431	1,615,442	1,606,410	893,018	883,431

This table examines whether financial distress outside of the Great Financial Crisis is associated with increased opioid prescribing. We consider two measures of financial distress. *1(Lag Provider House Price Change$\leq$-4%)* is an indicator for whether the provider's residential ZIP code experienced house price growth in the bottom decile of our sample during the previous year (corresponding to a maximum price change of -4% and a mean of -8%). *Provider Mortgage Foreclosure* is an indicator for whether the provider experienced mortgage foreclosure between years t$-$2 and t for prescriptions in t. Columns (1)-(4) use the ratio of opioid costs to total prescription costs as the dependent variable (*Opioid Cost / All Cost*); Columns (5)-(8) use the natural log of opioid costs (*Log Opioid Cost*) as the dependent variable. All specifications include provider fixed effects and provider practice city- or ZIP-by-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 6: Effect on Opioid Prescription by Provider Income

	Opioid Cost/All Cost				Log Opioid Cost			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lag Provider House Price Change	-0.025*	-0.019	-0.019	-0.016	-0.696***	-0.657***	-0.675***	-0.663***
	(-1.82)	(-1.42)	(-1.32)	(-1.13)	(-4.33)	(-3.96)	(-4.02)	(-3.79)
Lag Provider House Price Change ×	0.243***	0.209***	0.250***	0.216***	1.031***	0.876***	1.042***	0.881***
Lag Provider Income (std)	(19.93)	(16.82)	(20.03)	(16.89)	(10.76)	(8.29)	(10.74)	(8.19)
Lag Provider Income (std)	-0.011***	-0.008***	-0.012***	-0.009***	-0.061***	-0.047***	-0.063***	-0.050***
	(-9.27)	(-6.48)	(-9.41)	(-6.60)	(-5.06)	(-3.57)	(-5.06)	(-3.59)
Lag Provider House Price Change ×			-0.032**	-0.021			-0.244	-0.143
Lag Cost of Living (std)			(-2.36)	(-1.48)			(-1.50)	(-0.85)
Lag Cost of Living (std)			0.002				0.481*	
			(0.10)				(1.70)	
Provider FE	Y	Y	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y		Y		Y		Y	
Office Zip × Year FE		Y		Y		Y		Y
Y Mean	0.154	0.153	0.157	0.156	5.605	5.624	5.582	5.601
Y SD	0.212	0.211	0.214	0.213	2.490	2.490	2.482	2.483
X Mean	0.038	0.038	0.038	0.038	0.038	0.038	0.038	0.038
X SD	0.049	0.048	0.049	0.049	0.049	0.048	0.049	0.049
X 90Pct - 10Pct	0.109	0.107	0.111	0.109	0.109	0.107	0.111	0.109
N	347,822	335,734	324,701	312,837	347,822	335,734	324,701	312,837

This table examines whether the effect of healthcare providers' financial condition on the amount of opioids they prescribe varies by provider income. We match providers to occupation-location-level income data from the Bureau of Labor Statistics (BLS) for the previous year. *Lag Provider Income* is standardized to have a median of zero and a standard deviation of one. Columns (1), (2), (5), and (6) augment the main specification with an interaction between lagged house price change and lagged labor income. Columns (3), (4), (7), and (8) additionally include an interaction between lagged house price change and lagged Regional Price Parities (*Lag Cost of Living (std)*) from the Bureau of Economic Analysis (BEA), standardized in the same way as the labor income, to separate the role of income from geographic cost-of-living differences. *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 Prescriptions Stronger for Vulnerable Patients

	Opioid/All (1)	Log Opioid (2)	Opioid/All (3)	Log Opioid (4)
Lag Provider House Price Change	-0.017***	-0.441***	-0.001	-0.120*
	(-2.75)	(-6.34)	(-0.20)	(-1.70)
Lag Provider House Price Change ×	0.020***	0.350***		
Lag Office ZIP Median Log Income (std)	(4.09)	(7.39)		
Lag ZIP Median Log Income (std)	-0.003***	0.006		
	(-2.73)	(0.57)		
Lag Provider House Price Change ×			-0.039***	-0.360***
Lag Provider Non-White Patient Share (std)			(-8.51)	(-9.27)
Lag Provider Non-White Patient Share (std)			0.002**	-0.001
			(2.33)	(-0.33)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y	Y	Y	Y
Y Mean	0.122	6.498	0.117	6.683
Y SD	0.211	2.582	0.204	2.468
X Mean	0.027	0.027	0.027	0.027
X SD	0.056	0.056	0.056	0.056
X 90Pct - 10Pct	0.133	0.133	0.132	0.132
N	1,571,842	1,571,842	1,350,117	1,350,117

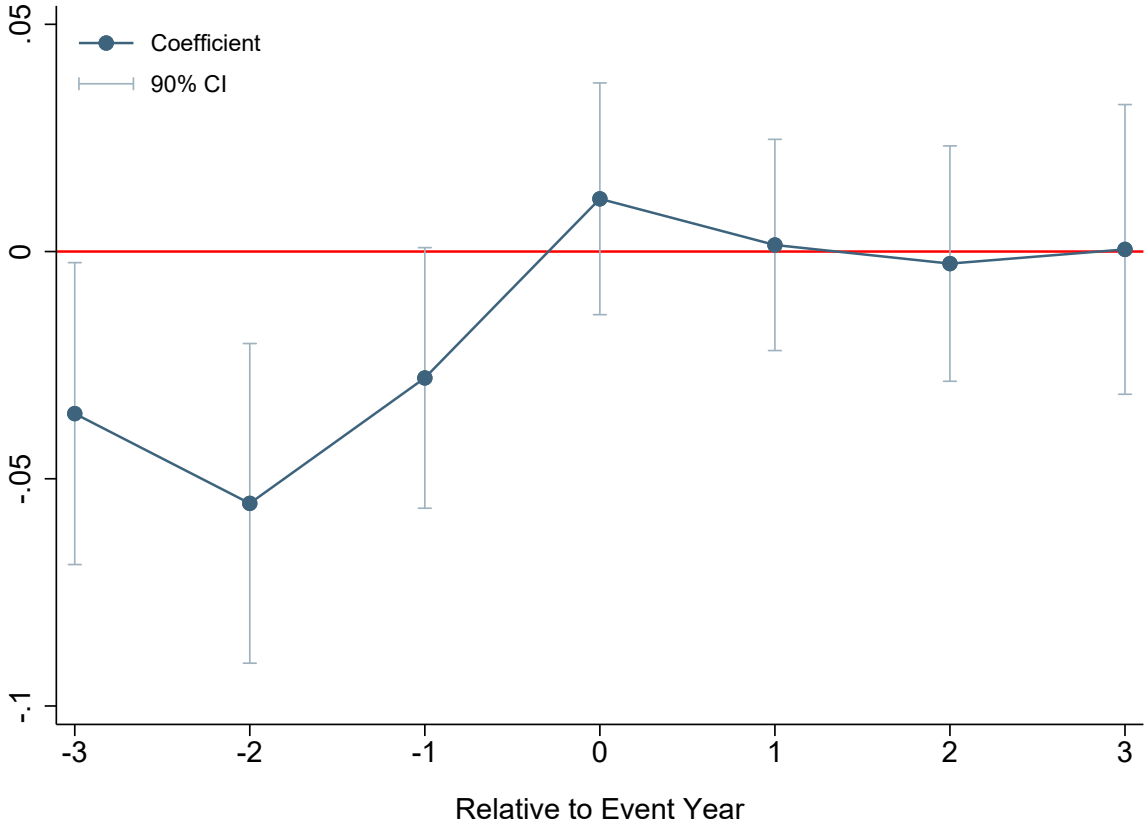
This table examines whether providers' opioid prescribing responses to house price changes vary with patient population characteristics. Columns (1)-(2) include an interaction term between providers' lagged house price change and the median log income of the provider's office ZIP code, measured using American Community Survey data. Columns (3)-(4) include an interaction term between providers' lagged house price change and the share of the provider's Medicare Part D beneficiaries who are non-white. Both median log income and the non-white patient share are standardized to have a median of zero and a standard deviation of one. The dependent variable is the ratio of opioid to total prescription costs in Columns (1) and (3), and the natural log of opioid prescription costs in Columns (2) and (4). *Lag Provider House Price Change* is the annual house price growth rate in the provider's residential ZIP code, 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 8: Effect of Provider House Price Changes on ADHD Prescriptions

	ADHD Cost/All Cost			Log ADHD Cost		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.009**	-0.007*	-0.005	-0.535*	-0.611*	-0.982*
	(-2.40)	(-1.77)	(-0.83)	(-1.74)	(-1.89)	(-1.84)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office × Year FE			Y			Y
Y Mean	0.011	0.011	0.009	3.654	3.661	3.640
Y SD	0.046	0.046	0.041	3.668	3.668	3.657
X Mean	0.044	0.044	0.044	0.044	0.044	0.044
X SD	0.040	0.040	0.039	0.040	0.040	0.039
X 90Pct - 10Pct	0.093	0.093	0.092	0.093	0.093	0.092
N	361,666	353,637	180,443	361,666	353,637	180,443

This table presents tests that examine the effect of healthcare providers' financial condition on the amount of ADHD drugs they prescribe, estimated using Equation 1. In Columns (1)-(3), the dependent variable is the share of ADHD drug costs relative to total prescribed drug costs. In Columns (4)-(6), the dependent variable is *Log ADHD Cost*, the natural logarithm of one plus the cost of ADHD drugs prescribed. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 (4) also include providers' office city–year fixed effects. Columns (2) and (5) also include providers' office ZIP–year fixed effects. Columns (3) and (6) include 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 Changes on Opioid Prescriptions Before and After Policy Intervention



This figure shows coefficient estimates from a stacked difference-in-differences regression examining the relationship between physicians' house price change and opioid prescribing behavior. The event year (0) represents when a state first adopted PDMP following the timing in Finkelstein et al. (2025). The dependent variable used in the regression is *Opioid/All Cost*. Estimates are shown for years relative to policy implementation, with 90% confidence intervals. We control for provider fixed effects and their practice ZIP–year fixed effects. Standard errors are corrected for clustering at the provider level.

Table A1: Provider House Price Changes, Patient Risk, and Opioid Prescriptions

	Patients' Avg Risk Score			Log Opioid Cost		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	0.013	0.014	0.017	-0.324***	-0.263***	-0.299***
	(0.93)	(0.98)	(0.84)	(-4.29)	(-3.46)	(-3.12)
Patients' Avg Risk Score				0.187***	0.181***	0.112***
				(14.81)	(14.52)	(7.17)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office × Year FE			Y			Y
Y Mean	1.462	1.463	1.506	6.387	6.391	6.575
Y SD	0.681	0.681	0.707	2.661	2.659	2.532
N	1,599,171	1,593,182	1,089,896	1,264,177	1,257,759	845,083

This table presents the regression estimates that examine the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 1, with additional controls for patients' health risk. Columns (1)-(3) regress providers' average patient HCC risk score on lagged house price growth. Columns (4)-(6) regress log opioid costs on lagged house price growth, controlling for contemporaneous patient risk scores. All specifications include provider fixed effects and varying levels of office location-by-year fixed effects. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 A2: Effect of Provider House Price Changes on Opioid-Related Payment from Pharmaceutical Companies to Provider

	1(Opioid Payment)		Log(Opioid Payment)	
	(1)	(2)	(3)	(4)
Lag Provider House Price Change	-0.036**	-0.036**	-0.090*	-0.091*
	(-2.46)	(-2.37)	(-1.77)	(-1.73)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y		Y	
Office Zip × Year FE		Y		Y
Y Mean	0.086	0.087	0.308	0.309
Y SD	0.281	0.281	1.036	1.037
X Mean	0.045	0.045	0.045	0.045
X SD	0.042	0.042	0.042	0.042
X 90Pct - 10Pct	0.096	0.096	0.096	0.096
N	736,223	728,983	736,223	728,983

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 columns (3) and (4), the dependent variable is the natural log of such payments plus one. *Lag Provider House Price Change* is the annual house price growth rate in the provider's residential ZIP code, 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 IA.1: Effect of Provider House Price Changes on Opioid Prescriptions: Including Providers who Never Prescribe Opioids

	Opioid Cost/All Cost			Log Opioid Cost		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.017***	-0.017***	-0.020***	-0.350***	-0.267***	-0.276***
	(-3.65)	(-3.64)	(-3.21)	(-6.56)	(-5.01)	(-4.11)
Sample Restriction						
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office × Year FE			Y			Y
Y Mean	0.090	0.090	0.095	4.760	4.761	5.132
Y SD	0.190	0.189	0.197	3.614	3.614	3.520
X Mean	0.032	0.032	0.032	0.032	0.032	0.032
X SD	0.053	0.053	0.053	0.053	0.053	0.053
X 90Pct - 10Pct	0.123	0.123	0.123	0.123	0.123	0.123
N	2,204,849	2,196,148	1,437,060	2,204,849	2,196,148	1,437,060

This table presents tests that examine the effect of healthcare providers' financial condition on the amount of opioids they prescribe, estimated using Equation 1 and including providers who never prescribe opioids. In Columns (1)-(3), the dependent variable is *Opioid Cost/All Cost*, the ratio of opioid prescription relative to total drug prescription in terms of total costs. In Columns (4)-(6), the dependent variable is *Log Opioid Cost*, the natural logarithm of one plus the cost of opioids prescribed. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 (4) include providers' office city–year fixed effects. Columns (2) and (5) include providers' office ZIP–year fixed effects. Columns (3) and (6) include 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 IA.2: Effect of Provider House Price Changes on Opioid Prescriptions: Robustness

Panel A: Opioid Prescription Scaled by All Drugs

	Opioids Days Supply/All Days Supply			Opioids Claims/All Claims		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.016***	-0.015***	-0.017**	-0.013**	-0.012**	-0.014**
	(-2.82)	(-2.72)	(-2.39)	(-2.52)	(-2.35)	(-2.23)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	0.115	0.115	0.120	0.178	0.178	0.185
Y SD	0.193	0.193	0.200	0.223	0.223	0.231
X Mean	0.027	0.027	0.028	0.027	0.027	0.028
X SD	0.056	0.056	0.055	0.056	0.056	0.055
X 90Pct - 10Pct	0.132	0.132	0.132	0.132	0.132	0.132
N	1,615,442	1,606,410	1,078,698	1,615,442	1,606,410	1,078,698

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 in Panel A are the ratio of opioid days supply relative to all days supply (*Opioids Days Supply/All Days Supply*); and the ratio of opioid claims relative to all claims (*Opioids Claims/All Claims*). The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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.

Panel B: Log Opioid Prescription and Indicator

	Log Opioid Days Supply			Log Opioid Claims			1(Opioid>0)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag Provider House Price Change	-0.453***	-0.346***	-0.322***	-0.279***	-0.204***	-0.187***	-0.052***	-0.048***	-0.034***
	(-6.96)	(-5.33)	(-4.10)	(-6.78)	(-4.99)	(-3.74)	(-6.54)	(-5.90)	(-3.32)
Provider FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y			Y		
Office Zip × Year FE		Y			Y			Y	
Office× Year FE			Y			Y			Y
Y Mean	6.255	6.258	6.397	3.995	3.997	4.083	0.940	0.941	0.947
Y SD	2.454	2.452	2.329	1.618	1.617	1.546	0.237	0.236	0.224
X Mean	0.027	0.027	0.028	0.027	0.027	0.028	0.030	0.030	0.031
X SD	0.056	0.056	0.055	0.056	0.056	0.055	0.054	0.054	0.054
X 90Pct - 10Pct	0.132	0.132	0.132	0.132	0.132	0.132	0.127	0.127	0.126
N	1,615,442	1,606,410	1,078,698	1,615,442	1,606,410	1,078,698	1,951,716	1,943,135	1,324,797

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 in Panel B are the opioid prescription amounts: *Log Opioid Days Supply*; *Log Opioid Claims*; and *1(Opioid>0)*, an indicator that equals one if the provider prescribes any opioid in that year. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 IA.3: Effect of Provider House Price Changes on Opioid Prescriptions: Poisson Regression

	Opioid Cost			Opioid Days Supply			Opioid Claims		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lag Provider House Price Change	-0.137**	-0.083	-0.116*	-0.149***	-0.094**	-0.124***	-0.140***	-0.086***	-0.094***
	(-2.49)	(-1.60)	(-1.80)	(-3.71)	(-2.55)	(-2.87)	(-4.13)	(-2.75)	(-2.65)
Provider FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y			Y		
Office Zip × Year FE		Y			Y			Y	
Office × Year FE			Y			Y			Y
Y Mean	6,243.674	6,252.300	6,246.359	3,343.492	3,347.299	3,329.315	155.060	155.231	156.427
Y SD	16654.999	16662.898	16055.080	6,945.311	6,947.017	6,654.931	270.861	270.891	259.907
X Mean	0.027	0.027	0.028	0.027	0.027	0.028	0.027	0.027	0.028
X SD	0.056	0.056	0.055	0.056	0.056	0.055	0.056	0.056	0.055
X 90Pct - 10Pct	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132	0.132
N	1,613,485	1,603,723	1,066,699	1,613,507	1,603,744	1,066,748	1,613,507	1,603,744	1,066,748

This table presents the Poisson regression estimates 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: *Opioid Cost*; *Opioid Days Supply*; and *Opioid Claims*. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 IA.4: Effect of Provider House Price Changes on Short-Acting Opioid Prescriptions

	Log Short-Acting Opioid Cost		
	(1)	(2)	(3)
Lag Provider House Price Change	-0.462***	-0.343***	-0.336***
	(-5.84)	(-4.33)	(-3.21)
Provider FE	Y	Y	Y
Office City × Year FE	Y		
Office Zip × Year FE		Y	
Office× Year FE			Y
Y Mean	6.190	6.193	6.359
Y SD	2.627	2.625	2.511
X Mean	0.032	0.032	0.033
X SD	0.053	0.053	0.052
X 90Pct - 10Pct	0.123	0.122	0.122
N	1,169,400	1,159,464	714,458

This table presents tests that examine the effect of healthcare providers' financial condition on the amount of short-acting opioids they prescribe, estimated using Equation 1. The dependent variables are the natural log of short-acting opioid drug prescription in terms of cost. The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, 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 IA.5: Effect of Provider House Price Changes on Patient Visits and Charges, without Controls

Panel A: House Price Change of the Last Year

	Log # Patient Visits			Log Submitted Charges		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.075***	-0.068**	-0.057	-0.059**	-0.051*	-0.033
	(-2.72)	(-2.43)	(-1.61)	(-1.99)	(-1.73)	(-0.89)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	5.784	5.786	5.817	10.863	10.866	10.939
Y SD	1.143	1.143	1.116	1.205	1.204	1.166
X Mean	0.044	0.044	0.044	0.044	0.044	0.044
X SD	0.041	0.041	0.041	0.041	0.041	0.041
X 90Pct - 10Pct	0.094	0.094	0.094	0.094	0.094	0.094
N	1,119,794	1,113,074	756,520	1,119,794	1,113,074	756,520

Panel B: House Price Changes of the Last Three Years

	Log # Patient Visits			Log Submitted Charges		
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.072**	-0.073**	-0.081*	-0.058*	-0.063*	-0.079*
	(-2.23)	(-2.24)	(-1.86)	(-1.66)	(-1.78)	(-1.69)
Lag2 Provider House Price Change	-0.121***	-0.095***	-0.129***	-0.112***	-0.082**	-0.125***
	(-3.79)	(-2.96)	(-3.00)	(-3.24)	(-2.36)	(-2.71)
Lag3 Provider House Price Change	-0.062**	-0.031	-0.046	-0.058*	-0.030	-0.036
	(-2.15)	(-1.04)	(-1.19)	(-1.86)	(-0.96)	(-0.88)
Provider FE	Y	Y	Y	Y	Y	Y
Office City × Year FE	Y			Y		
Office Zip × Year FE		Y			Y	
Office× Year FE			Y			Y
Y Mean	5.911	5.913	5.935	11.023	11.026	11.097
Y SD	1.077	1.076	1.051	1.145	1.144	1.104
X Mean	0.041	0.041	0.040	0.041	0.041	0.040
X SD	0.033	0.033	0.033	0.033	0.033	0.033
X 90Pct - 10Pct	0.080	0.080	0.079	0.080	0.080	0.079
N	653,401	648,301	420,650	653,401	648,301	420,650

This table examines the relationship using the same Medicare Part B data employed in Table 2. The dependent variables are the log number of patient visits (Columns 1-3) and log of charges submitted (Columns 4-6). The main independent variable is *Lag Provider House Price Change*, the annual house price growth rate in the provider's residential ZIP code, measured by the log difference of the Zillow Home Value Index (ZHVI) in the provider's residential ZIP code during the previous year. Panel B further includes annual growth rates of the provider's house price during the previous two and three years. We maintain provider fixed effects throughout, with location controls progressing from office city–year to office ZIP–year then to office–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 IA.6: Effect of Provider House Price Changes on Mortgage Foreclosure

	Provider Mortgage Foreclosure					
	(1)	(2)	(3)	(4)	(5)	(6)
Lag Provider House Price Change	-0.010***	-0.011***	-0.010***	-0.011***	-0.012***	-0.010***
	(-8.21)	(-4.70)	(-4.21)	(-7.13)	(-4.45)	(-3.76)
Provider FE				Y	Y	Y
Year FE	Y			Y		
Office City × Year FE		Y			Y	
Office Zip × Year FE			Y			Y
Y Mean	0.002	0.002	0.002	0.002	0.002	0.002
Y SD	0.046	0.045	0.045	0.045	0.045	0.045
X Mean	0.031	0.032	0.032	0.032	0.032	0.032
X SD	0.057	0.057	0.057	0.057	0.057	0.057
X 90Pct - 10Pct	0.136	0.137	0.136	0.136	0.136	0.136
N	1,129,053	1,108,662	1,100,102	1,122,259	1,101,320	1,092,505

This table examines the effect of lagged house price change among healthcare providers on mortgage foreclosure. *Provider Mortgage Foreclosure* is an indicator equals 1 if the provider's mortgage enters foreclosure in a year, and 0 otherwise. *Lag Provider House Price Change* is the annual house price growth rate in the provider's residential ZIP code, 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 IA.7: Effect on Opioid Prescription is Stronger for Vulnerable Patients (Without Imputation)

	Opioid/All (1)	Log Opioid (2)	Opioid/All (3)	Log Opioid (4)
Lag Provider House Price Change	-0.014**	-0.449***	-0.002	-0.203**
	(-2.49)	(-6.09)	(-0.45)	(-2.37)
Lag Provider House Price Change ×	0.012***	0.222***		
Lag Office ZIP Median Log Income (std)	(2.78)	(4.72)		
Lag ZIP Median Log Income (std)	-0.001	0.011		
	(-1.50)	(0.99)		
Lag Provider House Price Change ×			-0.006**	0.025
Lag Provider Non-White Patient Share (std)			(-2.45)	(0.44)
Lag Provider Non-White Patient Share (std)			-0.000	-0.011*
			(-0.46)	(-1.77)
Provider FE	Y	Y	Y	Y
Office City × Year FE	Y	Y	Y	Y
Y Mean	0.107	6.440	0.090	6.564
Y SD	0.186	2.637	0.157	2.592
X Mean	0.037	0.037	0.048	0.048
X SD	0.050	0.050	0.041	0.041
X 90Pct - 10Pct	0.114	0.114	0.093	0.093
N	1,374,663	1,374,663	901,326	901,326

This table examines whether providers' opioid prescribing responses to house price changes vary with patient population characteristics, without imputing the patient population characteristics. The sample in Columns (1)-(2) starts from 2012 and the sample in columns (3)-(4) starts from 2014. Columns (1)-(2) include an interaction term between providers' lagged house price change and the median log income of the provider's office ZIP code, measured using American Community Survey data. Columns (3)-(4) include an interaction term between providers' lagged house price change and the share of the provider's Medicare Part D beneficiaries who are non-white. Both median log income and the non-white patient share are standardized to have a median of zero and a standard deviation of one. The dependent variable is the ratio of opioid to total prescription costs in Columns (1) and (3), and the natural log of opioid prescription costs in Columns (2) and (4). *Lag Provider House Price Change* is the annual house price growth rate in the provider's residential ZIP code, 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.