Does Physicians' Financial Health Affect Medical Treatment and Patient Outcomes?

Yanhao Wang *

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Abstract

This paper studies how physicians' financial health influences treatment decisions and patient outcomes. I leverage a novel data set that links physicians' real estate portfolios to patient hospitalization records, and exploit within-physician variation in housing returns. In the context of childbirth where physicians have discretion and financial incentives to adopt C-sections over vaginal deliveries, I find that a one-standard-deviation decline in physician housing returns increases C-section rates by 1.6 percentage points, or 4 percent. However, patient health outcomes are not substantially affected. Evidence points to financial distress—rather than a standard wealth effect—as the primary mechanism behind this behavioral response.

JEL Codes: D14, G51, I11, I14, J44
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*Alberta School of Business, University of Alberta, Canada. Email: yanhao.wang@ualberta.ca. This paper is part of my doctoral dissertation (first draft: November 2023) and was previously circulated under the title "Wealth Shocks and Physician Behavior: Evidence from Childbirth." I am grateful to Haizhen Lin, Dan Sacks, Andrew Butters, Noah Stoffman, Isaac Hacamo, and Jia Xiang for their invaluable advice. I also thank Diane Alexander, Mike Baye, Jeff Clemens, Ginger Jin, Anthony Lo Sasso, Seth Freedman, Kosali Simon, Coady Wing and participants at the American Society of Health Economists Annual Conference, INFORMS Annual Meeting, International Industrial Organization Conference, Indiana University, and University of Alberta for their helpful comments. All errors are my own.

I Introduction

Spending on physician services is substantial and growing in developed countries (Martin et al., 2025). In the U.S., National Health Expenditure (NHE) on physician and clinical services increased by 7.4 percent, reaching $978 billion and about 3 percent of domestic GDP in 2023. Prior studies have shown that physician care provision is responsive to financial incentives in volume-based payment schemes (Clemens and Gottlieb, 2014; Brekke et al., 2017), and that physicians are tempted to adopt more profitable treatment options even when they do not necessarily align with patients' best interests (Gruber et al., 1999; Coey, 2015; Alexander, 2017). However, little is known about how physicians' own financial health influences their treatment decisions.

Although being some of the highest earners in the country (Gottlieb et al., 2025), physicians can be susceptible to various financial shocks. They often hold a considerable portion of their wealth in assets such as stocks and real estate. Volatile returns on these assets can expose them to unpredictable wealth losses and even create financial distress.[1] In addition, physicians, especially those early in their careers, often carry nontrivial personal debts, including student loans and mortgages. The health of their balance sheets can therefore be sensitive to shocks such as interest rate changes and shifts in student loan policies. For example, the One Big Beautiful Bill Act caps federal student loans for medical students at $200,000—roughly the median level of education debt but well below the median cost of attending four years of medical school (Association of American Medical Colleges, 2020)—raising concerns about its consequences for physicians' personal finance and care delivery.

This paper studies how physicians' financial health influences their treatment choices and the implications for patient outcomes. Prior research on physician financial incentives has relied on income shocks induced by policy reforms, such as changes in physician reimbursement rates (Clemens and Gottlieb, 2014; Alexander and Schnell, 2024; Cabral et al., 2025), which mixes income effect with substitution effect. In contrast, this paper turns to a less-explored yet important dimension of physicians' financial well-being—housing wealth—by bridging the literature of health care and household finance. Specifically, I leverage a unique data set that links physicians' real estate holdings to their treatment decisions, offering new evidence on how physicians respond to housing wealth shocks. Central to this empirical design is a large-scale database that covers nearly the entire universe of real estate transactions in the U.S., allowing me to track physicians' homeownership over time. I use the housing crisis during the Great Recession (2007–2009) as a natural experiment, which represents a substantial shock to physicians' financial health, given that households with incomes comparable to physicians typically hold around 20% of their wealth in real estate (Survey of Consumer Finance, 2009).

Directly estimating the causal effect on physician behavior presents an important empirical challenge—treatment choices could potentially be confounded by patient demand. For instance,

[1] According to Medscape's Physician Wealth and Debt Report (2021), about one-third of physicians experienced significant financial losses during the onset of the COVID-19 pandemic and the subsequent economic turmoil. Among specialists who admitted to investment mistakes, 44% reported losses from stock or real estate markets.

physicians in poorer financial health may treat patients with different risk profiles. To explicitly address this concern, I rely on hospital discharge records in Florida, which enables me to condition the identification on a detailed set of demand-side covariates at the patient level. I also focus on a high-stakes clinical setting—childbirth—which offers several advantages for this analysis. First, the major treatment margin in this inpatient context is well-defined: vaginal delivery versus cesarean section (C-section). Physicians in this setting (i.e., obstetricians and gynecologists, or OB-GYNs) exercise substantial discretion in recommending treatment options (Gruber et al., 1999; Johnson and Rehavi, 2016; Alexander, 2017). Second, C-sections generally pay 10%–20% higher professional fees than vaginal deliveries without requiring significantly more time input from physicians (Gruber and Owings, 1996; Corry et al., 2013). I therefore hypothesize that physicians in worse financial condition are more likely to respond to this financial incentive and perform C-sections, all else equal.

For the empirical analysis, I construct a time-varying, physician-level measure of cumulative housing returns, calculated as the change in average house values in the physician's zip code from the time of purchase to the time of treatment. Existing studies in household finance have used similar measures to proxy for households' wealth shocks and financial distress (Gerardi et al., 2018; Dimmock et al., 2021). I assume that physicians made their house-purchasing decisions prior to the financial crisis, which they could not have anticipated, so their subsequent housing returns are unlikely to correlate with patient treatment choices ex post. Under this assumption, I estimate a patient-level regression model that exploits quasi-experimental variation in housing returns, which is mainly driven by aggregate house price fluctuations over the business cycle, after conditioning on physician fixed effects (i.e., physicians' pre-determined housing portfolios).

Importantly, the physician fixed effects help control for time-invariant confounders at the physician level, such as risk preferences and surgical skills. To further address concerns about endogeneity, I augment the baseline specification with two additional sets of fixed effects. First, hospitals may experience contemporaneous financial shocks and have incentives to influence medical treatments (Dranove et al., 2017; Adelino et al., 2022). I therefore include hospital$\times$time fixed effects to account for potential parallel responses at the hospital level. Second, housing wealth shocks to physicians may correlate with those faced by their patients, potentially affecting healthcare utilization (Acemoglu et al., 2013; Tran et al., 2023) and underlying health status (McInerney et al., 2013; Schwandt, 2018). To rule out such demand-side channels, I further control for patient zip code$\times$time fixed effects in the regression.

As the main result, I find that a one-standard-deviation decrease in physicians' housing returns leads to a 1.6 percentage-point increase in the probability of C-section, which represents a 4% increase relative to the average. The effect is even more pronounced—2 percentage points, or 9%—among a subset of patients flagged as clinically low-risk and considered natural candidates for vaginal delivery. These results are economically meaningful and comparable to the effect of lowering the physician fee differential between C-sections and vaginal deliveries by about $250 (Gruber et al., 1999; Alexander, 2017; Foo et al., 2017), or that of increasing OB-GYN density by

26% (Gruber and Owings, 1996).

One might worry that the increase in the C-section rate is driven by physicians cherry-picking patients with certain risk profiles. To alleviate this concern, I show through a balance test that physicians' housing returns are conditionally independent of observed patient characteristics. I also consider the possibility that patients have unobserved preferences over certain providers by including a series of extended fixed effects in the regression. Another concern is that physicians disproportionately exposed to housing shocks may have incentives to perform more C-sections over time. To rule out this possibility, I show that the main results are insensitive to time-varying effects of physician characteristics such as tenure and gender. Finally, the findings are robust to alternative variable definitions, alternative model specifications, and a placebo test on non-homeowner physicians.

The average effect documented before could mask substantial heterogeneity. In fact, non-Hispanic Black patients are more than twice as likely to receive C-sections when their physicians experience a negative financial shock, suggesting that racial disparities may widen in economic downturns. I also find that patients whose expected medical benefits from C-sections and vaginal deliveries are similar (i.e., "marginal" patients) are more likely to be affected. The effect is also unequal for different physicians. Those who performed fewer excessive C-sections ex ante, who practice in more concentrated markets, and female physicians, are more responsive to lower housing returns.

As additional results, I find that the increase in C-section rates is concentrated in unscheduled C-sections as opposed to scheduled ones, which would not have been the case if medical necessity or maternal request were the primary reason for higher C-section rates. I also consider two assisted methods used during attempted vaginal deliveries—induction and vacuum/forceps. There is no evidence for reduced use of these ancillary procedures, indicating that physicians are not substituting C-sections for these less invasive options. One might also wonder if physicians increase the overall treatment intensity during the hospital stay. I find that there is indeed an increase, as proxied by hospital charges, but it appears to be largely explained by the difference in costs between C-sections and vaginal deliveries. Lastly, I find no evidence that physicians deliver more babies in response to negative financial shocks (i.e., the extensive margin).

A natural follow-up question is whether the increase in C-section use has any material impact on patient health. I present two sets of results concerning maternal outcomes. First, patients' average length of hospital stay increases slightly as a result of higher C-section rates. At the same time, patients are less likely to experience prolonged hospitalizations (more than 4 days for cesarean births or 2 days for vaginal births). Second, I examine a series of complications occurring during or shortly after childbirth (e.g., hemorrhage, infection, laceration, and other severe morbidities) and find no significant changes in the incidence of such adverse events. Taken together, these findings suggest that patient health is not substantially affected, at least for the metrics considered in this paper.

As the last part of the results, I explore the potential mechanisms through which financial shocks alter physicians' treatment choices. One possibility is a standard wealth effect: as housing wealth declines, physicians' marginal utility of income increases, incentivizing them to choose the more lucrative procedure (i.e., C-section). Alternatively, shrinking home equity and tighter liquidity constraints may limit physicians' financial flexibility and create financial distress. In this case, physicians may be especially motivated to recoup losses and avoid further costs, such as those of loan default, mortgage foreclosure, or even personal bankruptcy. I discuss these mechanisms using a discrete-choice framework for treatment decisions in childbirth, which incorporates two key motives behind physicians' behavior—financial incentives and patient welfare.

Evidence supports physician financial distress—rather than a standard wealth effect—as the primary mechanism underlying the higher C-section rate. First, positive wealth shocks should trigger the wealth effect but not financial distress. If the wealth effect were driving the results, one would expect C-section rates to decrease when house values rise. However, I find null effects during both the pre-crisis period (2004–2006) and the post-crisis recovery period (2013–2015). Second, if financial distress plays a role, the effect should be stronger when physicians' liquidity constraints are tighter. Consistent with this prediction, I find that responses of physicians under greater liquidity constraints—as proxied by high Loan-to-Value (LTV) ratios—are statistically and economically larger.

This paper speaks to several areas of research. First, it contributes to a burgeoning literature on how provider financial health affect medical treatment and patient outcomes. Previous studies have mostly focused on strategies of institutional providers in the face of financial shocks. For example, Aghamolla et al. (2024) find that hospitals exposed to credit rationing increase resource utilization but at a cost of care quality. Adelino et al. (2022) find that hospitals with greater investment losses from the financial crisis increase the use of more intensive treatments. Dranove et al. (2017) find that hospitals that experienced asset depreciation in the stock market did not increase prices but instead cut unprofitable service offerings. Gao et al. (2024) find that non-profit hospitals are better able to absorb financial pressures and maintain care quality compared to their for-profit counterparts.[2] To the best of my knowledge, this paper is the first to measure housing wealth shocks at the individual physician level.[3] In addition, my regression design controls for hospital×time fixed effects, helping to isolate physicians' responses from contemporaneous responses at the facility level.

More broadly, this paper adds to the literature on the real effects of household financial distress. Previous studies have shown that housing wealth shocks influence a wide range of household decisions, including but not limited to consumption (Mian et al., 2013), labor supply (Bernstein, 2021), fertility (Lovenheim and Mumford, 2013), education (Lovenheim, 2011), and political participation (McCartney, 2021). Financial distress has also been shown to affect workplace per-

[2]There are also related studies in the nursing home industry. For example, Antill et al. (2025) find that nursing homes under bankruptcy perform worse in staff turnover, health inspections, and patient hospitalization rates. Begley and Weagley (2023) find that nursing homes with tighter financial constraints under-invest in staffing and have more cases of COVID-19.

[3]A related paper is Erel et al. (2025), which studies how real estate shocks affect physicians' opioid prescriptions.

formance across various professions, such as innovative workers (Bernstein et al., 2021), teachers (Maturana and Nickerson, 2020), financial advisors (Dimmock et al., 2021), mutual fund managers (Pool et al., 2019), and equity analysts (Aslan, 2022). I delve into the labor market of physicians, who are high-income, highly skilled professionals and central to modern healthcare systems. I show that financial distress can potentially distort physicians' professional decision-making, creating externalities on public health. Importantly, the inpatient-level healthcare data allow me to control for rich characteristics about the downstream consumers, which is often unavailable in household finance research.

The fact that my analysis is centered around the Great Recession also connects this paper to the literature on how recessions affect health outcomes (Ruhm, 2000; Finkelstein et al., 2025). Prior work has examined effects of job displacement (Sullivan and Von Wachter, 2009), loss of health insurance (Cawley et al., 2015), and effects on mental health (McInerney et al., 2013; Currie and Tekin, 2015; Engelberg and Parsons, 2016; Schwandt, 2018). However, few papers look into the role of healthcare providers with the exception of Stevens et al. (2015), which documents cyclical fluctuations in the quality of nursing home care. My research enriches this literature by highlighting the supply-side channel and providing direct evidence on how financial shocks originating in the real estate market can have spillover effects on public health by changing physician behavior.

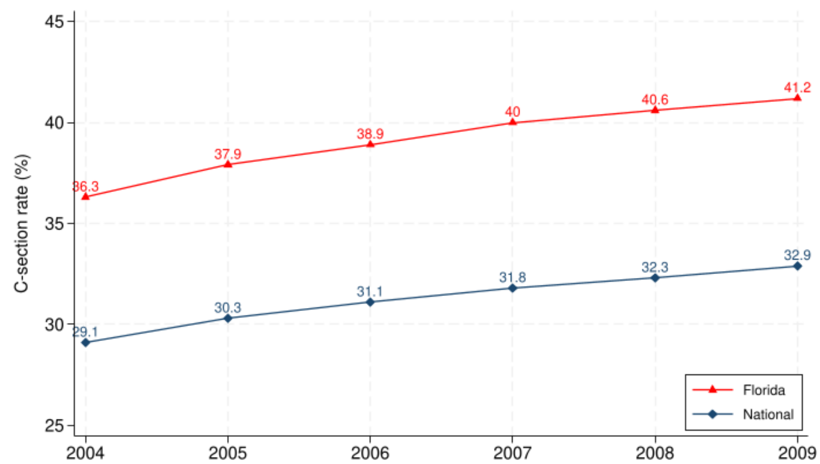
Finally, this paper advances the healthcare literature on physician-induced demand, particularly in the context of childbirth. Prior work has uncovered financial incentives (Gruber and Owings, 1996; Gruber et al., 1999), malpractice pressures (Wagner, 2000; Dranove and Watanabe, 2010), information asymmetry (Johnson and Rehavi, 2016), and technology adoption (Grytten et al., 2012) as drivers of high C-section rates. I contribute by introducing physician financial health as a previously overlooked factor and carefully discussing the underlying mechanisms. The finding that Black patients are especially vulnerable to physician inducement also resonates with recent work on racial disparities in health care (Singh and Venkataramani, 2022; Corredor-Waldron et al., 2024).

The remainder of the paper proceeds as follows. Section II describes the clinical setting. Section III introduces the data and empirical design. Section IV and V report the empirical results. I then discuss the underlying mechanisms in Section VI and finally conclude in Section VII.

II Setting

Childbirth is the most common cause of hospitalization in the U.S.—there are approximately 4 million newborns each year, accounting for 11% of all hospital stays and 4% of all inpatient hospital costs (Podulka et al., 2011). The primary treatment choice in childbirth is between vaginal delivery and cesarean section (C-section). Among all newborns in the U.S. nowadays, approximately one-third are delivered via C-section (Osterman et al., 2023). This C-section rate is double than the level in 1980, higher than those in most developed countries and exceeding the 10%–15% recommended by the WHO (Betrán et al., 2016). Geographic variations in C-section rates are also considerable across U.S. states (Baicker et al., 2006). For example, Figure 1 below shows that Florida's C-section rate has remained above 40% since 2007 and was among the highest in the U.S. by 2020.

Figure 1. C-section Rates in the U.S. and Florida



Notes: This figure shows C-section rates in the U.S. and Florida from 2004 to 2009. National rates are sourced from the CDC's Natality Database (`https://wonder.cdc.gov/natality.html`). Florida rates are calculated using hospital inpatient data from the Florida Agency for Health Care Administration (AHCA).

Clinically, many C-sections are performed at the discretion of physicians (Cunningham et al., 2014). Patients with clear risk factors (e.g., preterm birth, breech position, multiple fetuses, pinched or prolapsed umbilical cord) are usually recommended and scheduled for C-sections. Among all Florida patients who receive scheduled C-sections, about a quarter are perceived as low-risk.[4] Patients without well-defined medical indications will either attempt vaginal delivery or be induced into spontaneous labor. If complications such as "fetal distress" or "failure to progress" arise during labor, the physician may advise a C-section (i.e., an unscheduled C-section). The diagnosis of these complications and the decision of delivery method often fall into a clinical gray area and depend heavily on physicians' training, judgment, and preferences. Physicians must weigh the benefits and costs of a C-section for each patient and decide how long to allow labor to proceed (Kozhimannil et al., 2014). Patients, who often lack medical expertise, are generally unable to assess the appropriateness of these decisions, particularly given the limited time available. Insurers also grant physicians broad discretion in diagnosing conditions that justify a C-section.

Cesarean procedures can be life-saving for certain patients, especially for those with severe medical conditions. They can also save infants from the uncertainties of prolonged and difficult labor. On the other hand, although rarely leading to maternal mortality, C-sections may result in maternal morbidity, including adverse events such as infection, hemorrhage, and blood clots dur-

[4] Although not very common, scheduled C-sections can also be requested by patients (American College of Obstetricians and Gynecologists, 2019).

ing and after delivery. Due to their invasive nature, C-sections often require a longer hospital stay (2–4 days compared to 1–2 days for vaginal deliveries) and longer recovery time after discharge (6–8 weeks compared to 2–6 weeks for vaginal deliveries). C-section patients are more likely to be re-hospitalized and to require additional C-sections in future pregnancies. Finally, C-sections may negatively affect infants as well, causing injuries during delivery and increasing the risk of future respiratory and immune system issues.[5] The potential overuse of C-sections, especially for low-risk patients, has therefore raised concerns. Public health agencies and policymakers have advocated for reducing unnecessary C-sections. For instance, the Department of Health and Human Services (HHS) has set a target C-section rate for low-risk women of 23.6% by 2030 under the Healthy People Initiative, representing a significant reduction from the most recent level.

Financial incentives are cited as a key driver behind the rising adoption of C-sections (Gruber et al., 1999; Johnson and Rehavi, 2016; Alexander, 2017). The average physician fee for C-sections was about one-third higher than that for vaginal deliveries in the late 1980s (Gruber and Owings, 1996). More recently, using data from MarketScan during 2004–2010, Corry et al. (2013) estimates that both commercial insurers and Medicaid pay 10%–20% higher professional service fees for C-sections than for vaginal deliveries ($3,350 and $2,887 for commercial insurance, $1,654 and $1,445 for Medicaid).[6] While C-sections are more financially rewarding, they are not necessarily more labor-intensive. Vaginal deliveries often involve greater uncertainty in waiting time and require continuous monitoring during labor, which may last several hours. In contrast, C-sections typically take only 45–60 minutes, reducing opportunity costs and offering "convenience" to physicians (Keeler and Brodie, 1993).

Failure to perform a timely C-section is a common allegation in malpractice suits and can result in multimillion-dollar settlements. And therefore, C-sections are sometimes perceived as a legally safer option—a form of defensive medicine intended to demonstrate that "everything possible was done" to prevent potential harm. On the other hand, physicians are also able to hedge against these risks through malpractice insurance, and perhaps for this reason, previous studies have not found decisive evidence of a relationship between malpractice threats and C-section rates (Currie and MacLeod, 2008; Dranove and Watanabe, 2010; Frakes, 2013; Bertoli and Grembi, 2019).

Taken together, the clinical setting of childbirth is particularly useful as physician discretion plays a significant role in determining which medical treatment a patient receives. All else equal, C-sections tend to be more appealing to physicians than vaginal deliveries. Given these financial incentives, I hypothesize that physicians in weaker financial positions are more motivated to adopt C-sections and further discuss the potential mechanisms underlying this behavior in the empirical analyses that follow.

[5] Card et al. (2023) provides a summary of the clinical literature on maternal and infant health effects of C-sections.

[6] Physicians may also receive higher reimbursements from cesarean-related services (e.g., anesthesiology, laboratory, radiology, and pharmacy fees). There are separate financial incentives at the hospital level as well. For example, commercial insurers (Medicaid) paid an average of $9,933 and $6,738 ($4,358 and $3,102) for cesarean and vaginal deliveries as facility fees, respectively.

III Data and Empirical Design

III.A Data

To measure physician behavior and patient outcomes, I use de-identified hospital inpatient discharge data from the Agency for Health Care Administration (AHCA) of Florida. These data include patients insured by all payers and discharged by all hospitals in the state. For each inpatient discharge, it provides basic patient demographics, including age, race and ethnicity, gender, as well as diagnoses and procedures via ICD codes. These data also allow me to observe a series of patient outcomes, such as length of stay, discharge status, and hospital charges. I begin by extracting hospital inpatient records related to childbirth, and restrict the sample to patients aged 18 to 50, with a length of stay of no more than seven days, a Florida residence, and non-missing demographic information. Between the first quarter of 2007 and the fourth quarter of 2009, the dataset identifies 560,855 such childbirths, approximately 40% of which were delivered via C-section.

An key advantage of the Florida inpatient data is that they contain unique physician identifiers, allowing me to link each patient to the characteristics and real estate holdings of their attending physician. To obtain physician characteristics, I first link physicians to Florida's healthcare practitioner profiles using their professional license numbers. The practitioner profiles provide individual information such as full name and gender for all medical doctors in Florida. I then supplement these data with the National Provider Identifier (NPI) registry of the National Plan and Provider Enumeration System (NPPES), which contains additional physician-level information including specialty, age, and graduation date.

To measure physicians' real estate holdings, I rely on CoreLogic, a real estate database tracking housing transactions based on county deed records. CoreLogic has good coverage of property transactions dating back to the mid-1990s and has been used in household finance research (Bernstein et al., 2021; Aslan, 2022). For each deed record, the database reports the transaction date, sale price, property address, buyer and seller names, mortgage amount, mortgage term, interest rate, and other house characteristics. To match physicians with their houses, I restrict the sample to homes located in Florida and the property type to one of the following: single-family residence, condominium, commercial property, duplex, or apartment. I identify physician-owned properties by matching buyer or seller names with physician names using the combination "Last Name + First Name + Middle Name Initial." To reduce matching errors, I exclude physicians with common names and those matched with more than three properties. A physician is identified as the owner of a matched property from the date of purchase until the date of sale (if sold). Additional details on the matching procedure are provided in Appendix B.

To construct the final regression sample, I apply several filters. I begin by selecting medical doctors specializing in obstetrics and gynecology and excluding nurses and midwives. I then restrict the sample to physicians identified as homeowners by the end of 2006 and focus only on those who practiced continuously throughout the study period. Physicians in the bottom 1st percentile of delivery volume are considered inactive and dropped. I also drop patients whose physicians never performed a C-section, as well as those whose attending physicians differ from their operating physicians. This final step ensures that the analysis focuses on physicians capable of performing C-sections themselves, rather than having to rely on external surgeons.

In the main analysis, I restrict the sample period to the onset of the Great Recession (2007–2009), when house values declined most significantly. As an additional analysis to test whether the effects are symmetric, I also examine the preceding period (2004–2006) during which house prices rose almost universally and the recovery period (2013–2015) when house prices started to increase again after the crisis. Table 1 presents descriptive statistics for both the analytical sample of matched physicians and the leave-out sample of unmatched physicians. The matching procedures and filters described above identify 484 matched physicians who collectively delivered 187,873 births from 2007 to 2009.[7] Panel A of Table 1 shows that matched and unmatched physicians are fairly similar in terms of the patients they treat, regardless of patient demographics or risk factors.

Panel B of Table 1 further shows that matched physicians are similar also in terms of gender, tenure, workload, and C-section rate, compared to physicians with no matched properties. Regarding house characteristics, it is not uncommon for a matched physician to own multiple properties. By the end of 2006, 72% of the matched physicians owned one house, 21% owned two, and 7% owned three. 70% of all physicians have their primary houses in the same three-digit zip codes as their main hospitals, and 69% have their primary houses in the same three-digit zip codes where most of their patients reside. On average, physicians in the sample purchased their homes for about $544,000 (in 2006 constant dollars) and had owned them for approximately five years by the end of 2006.

III.B Measuring Financial Shocks to Physicians

The Great Recession offers a unique opportunity to examine how physicians' financial health influences their treatment decisions. Marked by a sharp decline in house prices, the crisis triggered substantial wealth shocks for homeowner physicians, weakening their financial standing. To capture this shock stemming from the real estate market, I follow the household finance literature and measure physicians' cumulative housing returns since the time of purchase. Specifically, for a physician j who purchased a home in zip code z at time t_0, their cumulative housing return at a later time t is defined as $R_{j,t} = \frac{HV_{j,t} - HV_{j,t_0}}{HV_{j,t_0}}$, where $HV_{j,t}$ denotes the house value at time t.

Because CoreLogic does not document a property's market value after purchase unless it is resold—–and such repeat sales are rare in the data—–I proxy subsequent home values using the Zillow Home Value Index (ZHVI) for zip code z at time t, denoted $ZHVI_{z,t}$.[8] When a physician owns multiple homes, I compute a weighted average housing return as in Equation (1) below.

[7] There are 368 unmatched physicians in the inpatient data. The resulting match rate is therefore about 60%, comparable to that in Bernstein et al. (2021), which uses a similar method to identify the residences of patent applicants.

[8] ZHVI measures the typical value of homes in the 35th to 65th percentile range of a local market. It is smoothed, seasonally adjusted, and available from 2000 onward. For earlier years, I impute values using the Federal Housing Finance Agency (FHFA) house price index. Appendix B provides details of this imputation.

Table 1. Summary Statistics

Sample	*Unmatched physicians*		*Matched physicians*	
	Mean	SD	Mean	SD
Panel A: Patient-level variables				
Individual characteristics				
Age	27.759	[5.997]	27.983	[5.975]
Black	0.195	[0.396]	0.212	[0.409]
Hispanic	0.217	[0.412]	0.193	[0.394]
Medicaid	0.495	[0.500]	0.444	[0.497]
Commercial	0.420	[0.494]	0.476	[0.499]
Weekend delivery	0.171	[0.376]	0.171	[0.377]
Individual risk factors				
Prior C-section	0.200	[0.400]	0.194	[0.395]
Malposition or malpresentation of fetus	0.046	[0.209]	0.046	[0.210]
35 years of age or older	0.154	[0.361]	0.159	[0.366]
Twins or more	0.016	[0.125]	0.017	[0.128]
Preterm	0.066	[0.248]	0.068	[0.252]
Asthma	0.027	[0.161]	0.026	[0.160]
Polyhydramnios or oligohydramnios	0.034	[0.180]	0.035	[0.183]
Physical abnormalities	0.059	[0.235]	0.059	[0.236]
Blood disorders or issues	0.021	[0.143]	0.022	[0.147]
Uterine size issues	0.227	[0.419]	0.229	[0.420]
Infant size issues	0.055	[0.228]	0.060	[0.237]
Obesity	0.024	[0.153]	0.025	[0.155]
Anemia	0.083	[0.276]	0.085	[0.278]
Malnutrition or insufficient prenatal care	0.245	[0.430]	0.247	[0.431]
Diabetes	0.061	[0.239]	0.062	[0.242]
Smoking, and alcohol or drug dependence	0.071	[0.257]	0.071	[0.257]
Infectious and parasitic conditions	0.030	[0.170]	0.031	[0.172]
Heart diseases	0.010	[0.099]	0.010	[0.102]
Fetal abnormality	0.013	[0.112]	0.013	[0.115]
Antepartum fetal distress	0.003	[0.055]	0.003	[0.059]
Hypertension	0.082	[0.275]	0.084	[0.277]
Isoimmunization	0.022	[0.147]	0.025	[0.155]
Premature rupture of the amniotic sac	0.031	[0.174]	0.031	[0.173]
Other complications of pregnancy	0.017	[0.128]	0.016	[0.127]
Aggregate risk indicators				
Low-risk	0.708	[0.455]	0.711	[0.453]
Predicted C-section risk	0.406	[0.334]	0.405	[0.332]
Treatment				
C-section rate (%)	41.055	[49.194]	40.179	[49.026]
Unscheduled C-section rate (%)	9.433	[29.228]	9.228	[28.941]
Observations	143853		187873	
Panel B: Physician-level variables				
Female	0.636	[0.482]	0.593	[0.492]
Tenure (as of 2006)	18.761	[9.810]	17.837	[8.949]
Number of deliveries per quarter	31.249	[22.278]	30.446	[20.807]
C-section rate (%)	41.896	[12.697]	41.492	[11.895]
Number of houses (as of 2006/12/31)			1.345	[0.603]
Occupancy (in years, as of 2006/12/31)			4.746	[4.341]
Purchase price of houses (in 2006 dollar)			544212.383	[389646.778]
Observations	368		484	

Notes: This table presents descriptive statistics for the regression sample of matched physicians and the leave-out sample of unmatched physicians, covering the time period from 2007 to 2009. Panel A reports patient-level variables, including demographics, individual risk factors, aggregate risk indicators, and treatments. Panel B presents physician-level variables, including physician demographics and housing characteristics (available only for matched physicians). Further details on data sources and sample construction are provided in Section III.A.

$$R_{j,t} = \sum_{z \in \mathbf{Z}_j} \phi_z \left(\frac{ZHVI_{z,t} - ZHVI_{z,t_0}}{ZHVI_{z,t_0}} \right) \tag{1}$$

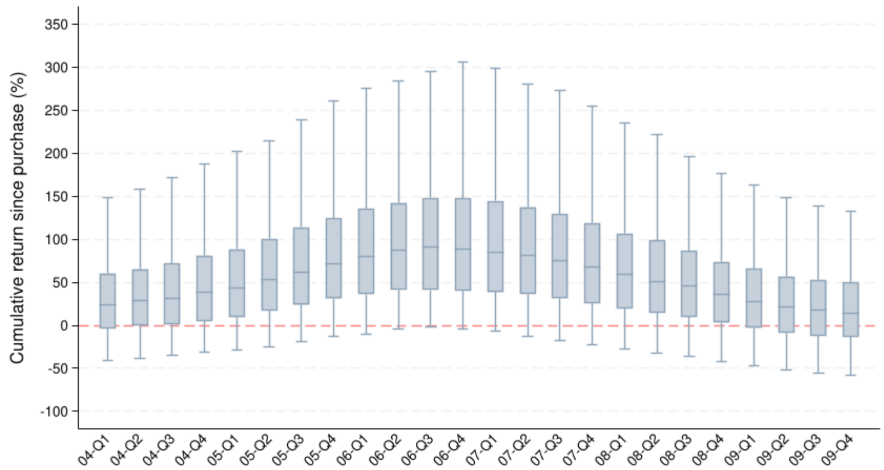
Here, $\mathbf{Z}_j$ represents the set of zip codes where physician j's houses are located. To avoid complications from strategic investment or divestment by physicians after the crisis began, I fix each physician's housing portfolio $\mathbf{Z}_j$ as of the end of 2006 and assume they hold it through the end of 2009 in the main analysis. The weight ϕ_z reflects the share of the house in zip code z in the physician's portfolio, calculated based on its inflation-adjusted purchase price.

The lower the cumulative housing return, the more negative the financial shock experienced by a physician. For example, an $R_{j,t}$ of -20% indicates that a physician has lost 20% of their home's value relative to the purchase price. This measure has several advantages. First, behavioral economists have emphasized the purchase price as a salient reference point for homeowners (Genesove and Mayer, 2001). This preference is especially relevant in my context as physicians are shown to have similar preferences (Rizzo and Blumenthal, 1996; Rizzo and Zeckhauser, 2003). Second, cumulative returns are strong predictors of negative home equity, offering insight into the potential channel through which financial distress may arise for physicians (Gerardi et al., 2018; Dimmock et al., 2021).

Importantly, cumulative returns capture a physician's exposure to real estate shocks by incorporating two physician-specific sources of heterogeneity. The first stems from the zip code(s) where physician j resides ($\mathbf{Z}_j$). Physicians' homes are scattered across different zip codes that exhibit heterogeneous housing price trends, even within the same recession period (Bogin et al., 2019). Physicians residing in more adversely affected zip codes experience larger depreciations in their real estate assets. To illustrate this, Appendix Figure A1 maps the number of physicians residing in each Florida zip code, while Appendix Figure A2 shows the variation in $ZHVI$ percentage changes across zip codes during 2007–2009. The second source of heterogeneity arises from the timing of home purchases (t_0). Physicians who bought homes earlier have accumulated more equity by paying down their mortgages and therefore have more "skin in the game" than those who purchased later at higher prices with less equity. Appendix Figure A3 displays the distribution of purchase years in the sample. Appendix Figure A4 highlights the implication of different purchase time by showing that physicians' cumulative returns declined more sharply had they purchased their homes earlier (e.g., in 2000) rather than later (e.g., in 2006). Combining these two dimensions of physician-level heterogeneity, $R_{j,t}$ is less likely to be confounded by unobserved factors that simultaneously influence patient demand, compared to market-level indicators of house price movement. I further elaborate the assumptions and tests for this argument later alongside the econometric specification.

Figure 2 summarizes the distribution of $R_{j,t}$ across physicians and over time. For the median physician, cumulative housing return reached about 90% by the last quarter of 2006, indicating that house values had almost doubled relative to purchase prices. However, there was considerable variation across physicians: at the same point in time, physicians at the 25th and 75th percentiles had cumulative returns of 40% and 148%, respectively. Most of these gains were wiped out by the end of 2009. By then, the average physician held just a 20% cumulative return, underscoring the severity of the recession-induced decline in housing wealth and the magnitude of the financial shocks used in this study.

Figure 2. Distribution of Physician Housing Returns



Notes: This boxplot shows the distribution of physicians' housing returns for each quarter from 2004 to 2009. Physician homeowners are identified using CoreLogic data. Housing returns are calculated as cumulative returns since the time of purchase, based on the Zillow Home Value Index, and are expressed in percentage points, as described in Section III.B. The center, top, and bottom lines of each box represent the 50th (median), 75th, and 25th percentiles of housing returns, respectively. The interquartile range (IQR) is the difference between the 75th and 25th percentiles. The upper and lower adjacent lines extend to 1.5 times the IQR above the 75th percentile and below the 25th percentile, respectively.

III.C Econometric Model and Identification

As a baseline specification, I estimate the following patient-level equation.

$$y_{i,j,h,t} = \beta R_{j,t} + \mathbf{X}_i\gamma + \mu_j + \delta_{h,t} + \eta_{c,t} + \varepsilon_{i,j,h,t} \tag{2}$$

where subscripts i, j, h, c, and t denote patient, physician, hospital, patient's zip code, and time, respectively. The Florida hospital inpatient data are reported quarterly, so unless otherwise noted, time t refers to the calendar year-quarter of childbirth. On the left-hand side of Equation (2), $y_{i,j,h,t}$ represents the main outcome variable of interest, $1\{C-section\}_{i,j,h,t}$, a binary indicator which equals one if patient i receives a C-section and zero if she receives a vaginal delivery. In addition to this measure of treatment choice, I also examine other margins that physicians can control during childbirth, as well as maternal health outcomes such as length of stay and morbidity. On the right-hand side, the key explanatory variable, $R_{j,t}$, represents the physician's housing return as of focal time t, as defined in Equation (1). To ease interpretation, I reverse the sign of $R_{j,t}$ in the regressions so that a positive estimate of $\hat{\beta}$ supports the hypothesis that physicians respond to negative wealth shocks by performing more C-sections. For the main analysis, I estimate Equation (2) using a linear probability model to allow inclusion of high-dimensional fixed effects and more straightforward interpretation of the coefficients, with standard errors clustered at the physician level.

This baseline specification controls for a comprehensive set of patient characteristics, $\mathbf{X}_i$, including demographics, insurance type, weekend delivery status, and clinical risk factors observed before labor (e.g., advanced maternal age, prior C-section, malposition of fetus, etc). These risk factors help adjust for the medical appropriateness of procedures, ensuring that the analysis compares treatment choices among clinically similar patients. Summary statistics for these covariates are reported in Table 1. Appendix Table A1 shows that most of them are strong predictors of C-section risk.[9]

Physicians may differ in their skills—some may be more proficient at performing C-sections or at diagnosing patients who require them (Epstein and Nicholson, 2009; Currie and MacLeod, 2017). Therefore, Equation (2) includes physician fixed effects, μ_j, to capture such persistent differences in practice style and physician preferences. One might also worry that physicians with certain unobserved characteristics systematically sort into areas that experienced steeper house price declines or tend to purchase their homes around the same time. Physician fixed effects address these concerns by accounting for physicians' housing portfolios (including both the choice of location and the time of purchase), which are fixed prior to the onset of the Great Recession by construction. The remaining within-physician variation in housing returns is primarily driven by house price movements at more aggregate levels.

I also include two sets of fixed effects to address potential endogeneity concerns. The first relates to a parallel supply-side channel. Specifically, prior research has documented substantial variation in C-section rates across hospitals (Kozhimannil et al., 2013; Card et al., 2023; Robinson et al., 2024), and found that hospital practices are sensitive to financial shocks (Dranove et al., 2017; Adelino et al., 2022). If physicians who experience larger wealth shocks disproportionately work in hospitals with systematically higher or lower C-section rates—or are influenced by hospital-level incentives—the estimate of β may be biased. To address this, I include hospital$\times$year-quarter fixed effects, $\delta_{h,t}$, which helps to isolate supply-side responses at the individual physician level from those at the facility level.

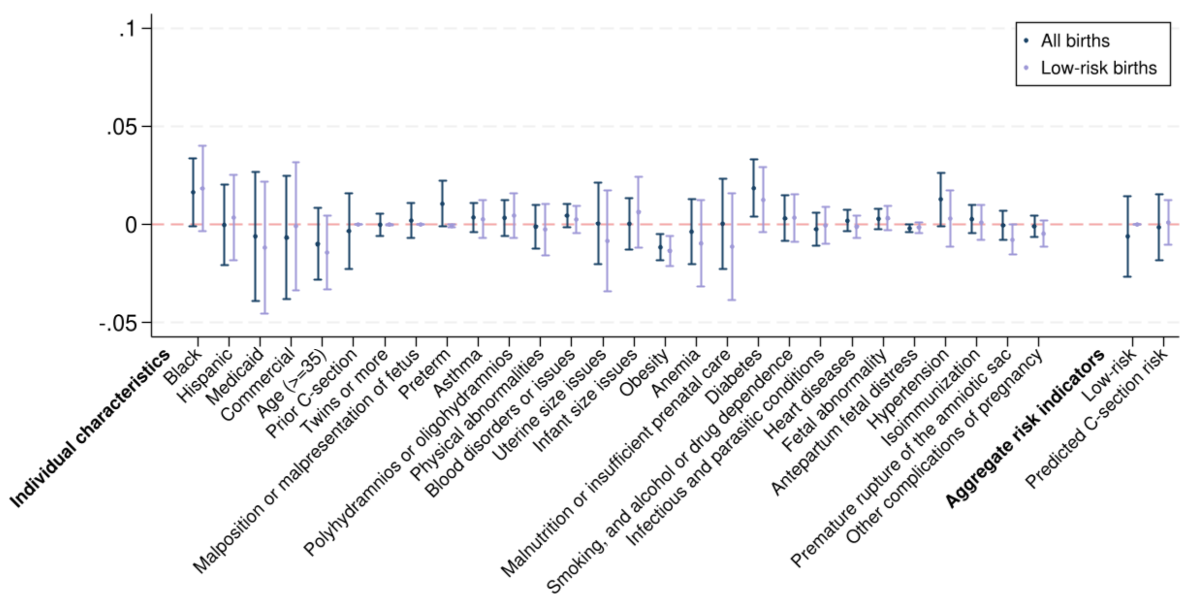
The second concern arises from confounding demand shocks. For instance, existing research has shown that wealth or income shocks can affect households' healthcare utilization and spending (Acemoglu et al., 2013; Tran et al., 2023), and can even impact physical and mental health (McInerney et al., 2013; Schwandt, 2018). If physicians exposed to greater financial shocks tend to treat patients from recession-affected zip codes–where health conditions may have worsened–the estimated effect on physician behavior could be biased upwards. To account for such time-varying latent demand, I include patient zip code$\times$year-quarter fixed effects, $\eta_{c,t}$, in Equation (2). This is feasible not only because patients' residential zip codes are directly available in the Florida inpatient data, but also because only 5% of patients are from the same zip code as their physicians.

[9]Similar risk factors are also used by previous studies (Henry et al., 1995; Gregory et al., 2002; Johnson and Rehavi, 2016; Currie and MacLeod, 2017; La Forgia, 2022).

The identification of Equation (2) relies on the conditional independence assumption. That is, conditional on patient covariates and fixed effects at the physician, hospital×year-quarter, and patient zip code×year-quarter levels, patients' potential treatments are mean independent of physicians' housing returns. In other words, after controlling for these covariates and fixed effects, patients paired with different physicians should not systematically differ in their observed characteristics. I assess this assumption by testing whether patient covariates are balanced across physician real estate shocks.

First, I regress each of the patient characteristics in $\mathbf{X}_i$ on physician housing return, including the fixed effects controlled for in Equation (2). Figure 3 presents the estimated coefficients for physician housing returns from these individual regressions—they are generally close to zero and statistically insignificant.[10] I also run a reversed regression with physician housing return as the dependent variable and all patient risk factors as independent variables. A joint test on these risk factors produces an F-statistic of 1.5, failing to reject the null hypothesis that all risk factor coefficients are zero at the 5% significance level.

Figure 3. Balance Test for Patient Characteristics



Notes: This figure presents the results of the balance test, as described in Section III.C. Coefficient estimates and 95% confidence intervals from separate regression of patient characteristics on physician housing returns (reversed in sign) are reported. Patient Characteristics include patient demographics, individual risk factors, and aggregate risk indicators. Physician housing returns are calculated as cumulative returns since the time of purchase. All regressions include fixed effects in the baseline specification. The test is performed on both the full sample of all births and a subsample of low-risk births. Both samples cover the period from 2007 to 2009.

I also test whether aggregate risk indicators correlate with physicians' real estate shocks. I consider two such aggregate risk indicators. The first one is a clinical low-risk status flagged by a few key risk factors according to the guidelines of the Agency for Healthcare Research and

[10] The only two exceptions are obesity and diabetes, but they correlate with housing returns in opposite directions.

Quality (AHRQ); the second one is C-section risk predicted using all patient characteristics and a Logit model.[11] Columns (1) and (2) of Appendix Table A2 show that neither of these aggregate risk factors can be significantly predicted by physicians' housing returns. To further test whether these risk measures are correlated with the underlying variation in physicians' housing returns, I define two indicators for: (1) whether a physician lives in a more affected zip code (i.e., zip codes with changes in the house value index over 2007–2009 greater than the median), and (2) whether a physician purchased their home relatively early (i.e., before the median purchasing year). Columns (3) to (6) of Appendix Table A2 report that neither of these indicators can significantly predict patient risks. Overall, these tests suggest that patient characteristics are largely balanced across physicians exposed to different levels of financial shocks, lending credibility to the conditional independence assumption.

The identification also requires that other unobserved physician characteristics that may affect patient treatments are conditionally mean-independent of physician housing returns (i.e., the exclusion restriction). A violation of this assumption could arise if physicians with certain characteristics end up performing more C-sections over time while also involuntarily being exposed to disproportionately greater shocks. For example, junior physicians who tend to buy homes later may become more proficient at diagnosing patient conditions and rely less on C-sections as they gain experience. It is worth noting that the inclusion of physician fixed effects alongside year-quarter fixed effects already absorbs time-varying physician characteristics that evolve *linearly* over time, such as age or years of experience, even if they are not explicitly included in the model. As an additional test (Appendix Table A4), I further show that explicitly controlling for the *nonlinear* effects of physician characteristics (e.g., tenure and gender) does not affect the results.

Taken together, it is unlikely that physicians' housing decisions made *ex ante* are correlated with factors that influence patient treatment *ex post*. Although one might worry that physicians could have anticipated the housing crisis and made strategic investment or divestment decisions, prior studies such as Cheng et al. (2014) have shown that even financial professionals failed to foresee the housing bust—let alone medical students and physicians, who are reportedly less financially literate (Jayakumar et al., 2017; Igu et al., 2022).[12]

IV Main Results

This Section provides the main empirical results. I start by estimating the effect of physicians' financial health on the major treatment margin—vaginal delivery versus C-section—in subsection IV.A. To strengthen the evidence, I then report a battery of additional tests in subsection IV.B.

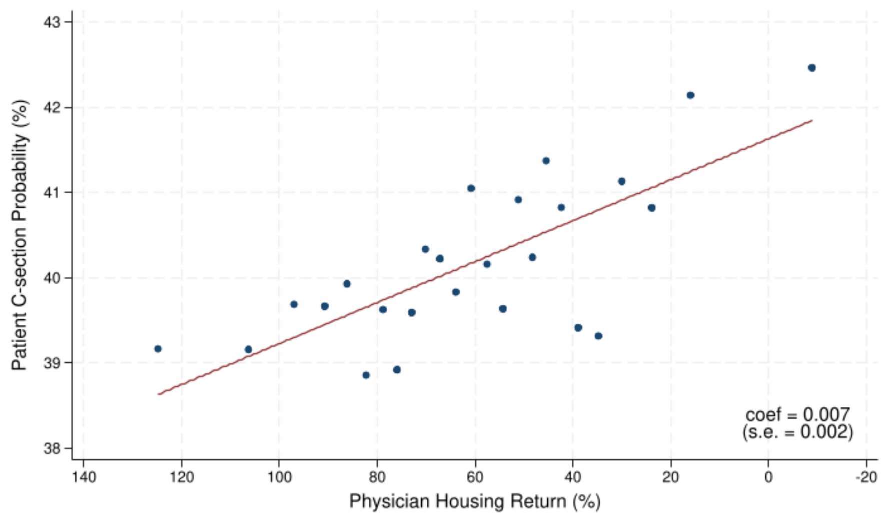
[11] I discuss these two aggregate risk indicators in greater details later in Sections IV.A and V.A, respectively.

[12] Additional tests also confirm that physicians more affected by the housing shocks did not practice differently compared to their less-affected peers prior to the crisis.

IV.A Effects on C-section Rate

Before delving into the regression analysis, I present model-free evidence on the relationship between physicians' housing returns and C-section rates. Specifically, I first residualize both physicians' housing returns and C-section rates with respect to physician fixed effects. I then group the residualized observations into equal-sized bins based on housing return and compute the average C-section rate within each bin. Figure 4 visualizes this relationship using a binscatter plot. The fitted line shows that the C-section rate increases as physician housing return decreases, suggesting that physicians are more likely to perform C-sections when they experience greater losses in housing wealth.

Figure 4. Relationship Between C-section Rate and Physician Housing Return



Notes: This binscatter plot provides model-free evidence on the relationship between C-section rates and physician housing returns using data from 2007 to 2009. Patients are grouped into 25 equal-sized bins based on their physicians' cumulative housing returns since purchase (expressed in percentage points), shown on the horizontal axis. The average C-section probability for each bin is plotted on the vertical axis. Both C-section probabilities and housing returns are residualized against physician fixed effects. The red solid line represents a linear fit estimated over the binned averages, with the slope coefficient being 0.007 (s.e.=0.002).

To further investigate how financial shocks influence treatment decisions, I estimate linear regressions as in Equation (2) using patient-level data. The primary outcome variable is a binary indicator for whether a patient receives a C-section as opposed to a vaginal delivery from her physician. For ease of interpretation, I scale the outcome variable by 100. The key explanatory variable is the physician's cumulative housing return, which is reverse-coded so that a positive estimate of β reflects a higher C-section rate in response to negative housing shocks. Panel A of Table 2 presents the results, with additional fixed effects added progressively across columns. Column (1) includes patient covariates, year-quarter fixed effects, and physician fixed effects. The coefficient on physician housing return is positive and statistically significant, indicating that greater financial losses are associated with a higher probability of C-section, holding other factors constant. Column (2) adds hospital$\times$year-quarter fixed effects to account for hospital-level incentives and responses. The estimated effect becomes larger in magnitude and more statistically significant.

Higher C-section rates may not reflect changes in physician behavior but instead result from physicians with larger financial shocks disproportionately treating sicker patients who require C-sections. The rich set of patient characteristics controlled in the regressions have helped to alleviate this concern. Nevertheless, the role of selection on unobserved characteristics remains an open question. One such possibility is that patients, concurrently affected by the housing crisis, develop worse health conditions which are not captured by the risk factors. If patients' financial shocks are positively correlated with those of their physicians, the estimated physician response could be overstated.

To address this, the preferred specification—Column (3) of Table 2—further includes patient zip code×year-quarter fixed effects to account for time-varying local socio-economic conditions (e.g., declining household earnings and property values on the patient side) that could be both correlated with physicians' financial shocks and consequent to patients' underlying health. The estimated coefficient remains statistically significant and similar in magnitude. To put the estimate ($\hat{\beta}$=2.379) into perspective, a one-standard-deviation decrease in physicians' cumulative housing returns (≈ 0.66) leads to an increase of 1.6 percentage points in the overall C-section rate, which amounts to a 4% increase relative to the average (40.18 percentage points).

This effect is economically meaningful. Compared to studies that exploit variation in physician fees between C-sections and vaginal deliveries (Gruber et al., 1999; Alexander, 2017; Foo et al., 2017), it is equivalent to the effect of lowering the physician fee differential by about $250.[13] Gruber and Owings (1996) use increases in physician density to proxy for negative income shocks. Based on their estimate, the effect in my study is comparable to increasing the OB-GYN density by about 26%. My result is also of similar magnitude to other estimates in the literature. For example, it is equivalent to about 65% of the gap in C-section rates between physician mothers and non-physician mothers (Johnson and Rehavi, 2016), and about 1.25 times the effect of OB-GYNs being acquired by physician practice management companies (La Forgia, 2022).

Finally, in Column (4) of Table 2, I reestimate the model without the patient covariates. The magnitude and significance of β remain highly similar, suggesting that the main result is not likely driven by selection on observed patient characteristics. This is also consistent with the finding that patient chacrteristics are balanced across physicians (Figure 3 and Appendix Table A2). As part of the additional tests, I further show that the main result stays even accounting for more granular two-way matching between patients and physicians.

[13]Specifically, using within-state and over-time variation in Medicaid's pay differential between cesarean and vaginal deliveries (1988–1992), Gruber et al. (1999) estimate that a $100 increase in the fee differential leads to a 0.7 percentage point rise in the C-section rate. Using a similar empirical strategy but more recent state-level Medicaid data (1990–2008), Alexander (2017) estimates that the C-section rate increases by 0.6 percentage points as the pay differential increases by $100. Using data from private insurers in California, Foo et al. (2017) also estimate that a $100 increase in the pay differential results in a 0.6 percentage point increase in the C-section rate. Based on these estimates, a 1.6 percentage point that I estimate is thus equivalent to the effect of lowering the pay differential by about $\frac{1.6}{(0.7+0.6)/2} \times \$100 \approx \$250$.

Table 2. **Effects on Treatment Choices**

Panel A: All patients				
	C-section			
	(1)	(2)	(3)	(4)
Physician housing return	1.615	2.383	2.379	2.450
	(0.834)	(0.965)	(1.023)	(1.257)
Year-quarter FE	✓			
Patient covariates	✓	✓	✓	
Physician FE	✓	✓	✓	✓
Hospital×year-quarter FE		✓	✓	✓
Patient zip code×year-quarter FE			✓	✓
Mean (dep. var.)	40.18	40.18	40.18	40.18
Observations	187,873	187,873	187,873	187,873

Panel B: Low-risk patients				
	C-section			
	(1)	(2)	(3)	(4)
Physician housing return	2.356	3.352	3.130	3.202
	(1.026)	(1.179)	(1.253)	(1.284)
Year-quarter FE	✓			
Patient covariates	✓	✓	✓	
Physician FE	✓	✓	✓	✓
Hospital×year-quarter FE		✓	✓	✓
Patient zip code×year-quarter FE			✓	✓
Mean (dep. var.)	22.71	22.71	22.71	22.71
Observations	133,551	133,551	133,551	133,551

Notes: This table reports baseline results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The outcome variable is a binary indicator for C-section and scaled by 100. All columns control for physician fixed effects. Columns (1)–(3) include patient characteristics, including demographics, insurance type, weekend delivery, and clinical risk factors based on comorbidities observed prior to labor onset. Column (2) additionally includes hospital×year-quarter fixed effects. Column (3) additionally includes patient zip code×year-quarter fixed effects. Column (4) drops patient characteristics from the regression. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are are reported in parentheses.

In Panel B of Table 2, and throughout much of the subsequent analysis, I replicate the results using a subsample of *low-risk* patients. Following the guidelines of the Agency for Healthcare Research and Quality (AHRQ), low-risk patients are defined as those without indications of prior C-section, hysterotomy, abnormal presentation, preterm delivery, fetal death, multiple gestation diagnoses, or breech birth.[14] Low-risk patients are generally considered candidates for vaginal delivery, making additional C-sections in this group more likely to be medically unnecessary and thus a public health concern (Hartmann et al., 2012). Compared to the estimates in Panel A, the

[14]See AHRQ's Inpatient Quality Indicator 33 (IQI 33). The same criteria is used by La Forgia (2022). I also test an alternative definition of low-risk births based on predicted C-section probability cutoffs, which yields similar results.

effects among low-risk patients are statistically stronger and larger in magnitude. For example, in Column (3) of Panel B ($\hat{\beta} = 3.130$), a one-standard-deviation decrease in physicians' cumulative housing returns (≈ 0.65) results in a 2 percentage point increase in the C-section rate among low-risk patients, which is equivalent to a 9% increase relative to the sample mean. Taken together, these results provide additional evidence against the alternative explanation that demand-side factors are driving the observed increase in C-section rates.

IV.B Additional Tests

Results of several additional tests are summarized in Appendix Tables A3 to A7. I begin by adding extended fixed effects to the baseline specification to rule out the possibility that the main results are driven by alternative selection channels. I then show that additionally controlling for time-varying effects of some physician characteristics does not affect the main results. I also consider a range of alternative measures of physician financial shocks, as well as alternative sample and model specifications, all of which yield consistent results. Finally, I confirm in a placebo test that non-homeowner physicians are not responsive to housing shocks.

Other Selection Channels. The baseline specification has attempted to rule out alternative explanations from both the supply side and the demand side by conditioning the identification on a rich set of patient covariates and fixed effects at the physician, hospital$\times$year-quarter, and patient zip code$\times$year-quarter levels. Nonetheless, a more nuanced concern remains: patients with unobserved preferences may selectively choose certain providers that are systematically more or less exposed to housing wealth shocks. Such "two-way" selection between patients and providers could bias the estimates if it exists.

I first assess whether *patient-hospital* matching may be driving the main results. To do so, I focus on a subsample of patients who live close to the hospitals where they deliver, restricting the distance between the patient's residential zip code and the hospital's zip code to no more than 10 miles. These patients are more likely to select hospitals based on geographic proximity rather than unobserved preferences or other confounding factors. Column (1) of Appendix Table A3 shows that the estimate remains highly significant within this restricted sample. Alternatively, I also try to include patient zip code$\times$hospital fixed effects on top of the baseline specification, which absorb all time-invariant factors specific to each patient zip-hospital pair. Column (2) of Appendix Table A3 shows that the estimate is similar.

Next, I consider the possibility of *patient-physician* matching. To examine this, I focus on a subset of patients who live far from their physicians by requiring that the patient's 3-digit zip code differs from that of their physician. These patients are arguably less likely to have a prior relationship with their physicians or to possess any information about their physicians' financial health in advance. Column (3) of Appendix Table A3 shows that the result remains robust within this subsample. Similarly, I also try to include patient zip code$\times$physician fixed effects to control for time-invariant factors specific to each patient zip-physician pair. Column (4) of Appendix

Table A3 reports a similar finding.

Finally, *physician–hospital* matching may also play a role, as prior research has shown that physician performance can be hospital-specific and there is notable performance dispersion among physicians even within the same hospital (e.g., Mourot, 2025). In practice, such differences may stem from physicians' hospital privileges, employment affiliations, or other factors in their production functions. The policy implications would differ if the results merely capture physicians reallocating C-sections across hospitals, rather than reflecting a broader shift in their practice styles. To address this concern, Column (5) of Appendix Table A3 restricts the sample to physicians who practice at only one hospital during the study period (i.e., "single-homing" physicians). Column (6) further includes physician×hospital fixed effects in the regression. In both cases, the results remain consistent with the baseline estimates.

Time-Varying Effects of Physician Characteristics. Physician fixed effects included in the baseline specification help control for time-invariant physician characteristics such as practice styles and risk preferences. Together with year-quarter fixed effects, they also absorb time-varying physician characteristics that evolve *linearly* over time, such as age or years of experience. However, one might suspect that physicians' experience may accumulate *non-linearly* and thus confound the financial shocks that physicians face. I therefore consider several different functional forms of such non-linear effects of physician characteristics such as tenure and gender.

A physician's tenure is measured as the number of years from medical school graduation to the focal year. I include the following functional forms of physician tenure as additional controls in the regression: (1) the logarithm of physician tenure, (2) the exponential of physician tenure, and, more flexibly, (3) physician tenure×year-quarter fixed effects. The results, reported in Columns (1)–(3) of Appendix Table A4, remain similar to the baseline estimates. It is also possible that physicians of different genders may face disproportionate financial shocks and develop different practice styles over time. I therefore include physician gender×year-quarter fixed effects in the regression as an additional check. Column (4) of Appendix Table A4 confirms that the main effect still holds.

Alternative Measures of Physician Financial Shocks. In the main analysis, I measure physician financial shocks using cumulative housing returns since the time of purchase. Here, I consider four alternative measures. First, one might be concerned that physicians' responses to real estate shocks are not instantaneous. To address this, I use the same cumulative housing return since purchase but *lagged by one quarter* as the main independent variable. Column (1) of Appendix Table A5 presents the result using this lagged measure. The estimate remains statistically significant and closely aligns with the baseline result.

Second, physicians may place greater weight on more recent changes in house values. To capture this, I use the cumulative housing return over the past quarter as a measure of housing wealth shocks. Column (2) of Appendix Table A5 shows that a decline in this *quarter-over-quarter* return also predicts an increase in C-section rates. I then extend the return window by constructing a *year-over-year* housing return, following related studies such as Bernstein et al. (2021) and Dimmock et al. (2021). The result, presented in Column (3) of Appendix Table A5, is again consistent with the main hypothesis.

Lastly, I use the logged level of *house prices* as the main independent variable in the regression. The value of an individual house is not directly observed in CoreLogic except at the time of transaction. Instead, I compute the house price as the (inflation-adjusted) purchase price multiplied by the cumulative housing return since purchase. Column (4) of Appendix Table A5 presents the result: C-section rates increase as physicians' house prices decline. The coefficient on logged house prices can also be interpreted as the semi-elasticity of the C-section rate. For example, in the low-risk subsample, a 10% decrease in house prices corresponds to an increase of 0.3 percentage points in the probability of a C-section.

Alternative Sample and Model Specifications. In the main analysis, I focus on physicians who remained actively practicing throughout the sample period and are thus less likely to be affected by employment or unemployment shocks beyond changes in housing wealth. However, physicians at earlier or later stages of their careers may differ in preferences or behavior. Does the result depend on excluding these physicians? To examine this, I relax the sample restrictions to include physicians who entered the labor force after the recession began in 2007 (i.e., late entries), as well as those who retired before 2009 (i.e., early exits). The result, reported in Column (1) of Appendix Table A6, shows little change compared to the baseline estimates.

As noted earlier, I fix each physician's housing portfolio as of the end of 2006 when calculating their housing returns and assume the portfolio is held through the end of 2009. This restriction implies that the main analytic sample includes only physicians identified as homeowners no later than 2006. However, some physicians may have purchased homes after the onset of the crisis or sold their properties before it ended. To assess whether the results are sensitive to this restriction, I allow for varying homeownership over time and track physician housing returns accordingly. The result, shown in Column (2) of Appendix Table A6, remains similar to the baseline estimates.

Lastly, instead of clustering standard errors at the physician level as in the main analysis, Columns (3)–(5) of Appendix Table A6 report estimates with standard errors clustered at more conservative levels, including the hospital, patient zip code, and physician zip code. These alternative clustering levels do not affect the main results.

A Placebo Test. So far, I have relied on housing shocks during the real estate crisis to identify the effect of physicians' financial health on their treatment choices. However, not all physicians were homeowners at the onset of the crisis. Non-homeowner physicians should arguably be insensitive to decline in housing values. In other words, if I were to run the same regression on a separate sample of non-homeowner physicians, I should expect no effect on their C-section rates.

There are 368 physicians who are not matched with any real estate transaction records (Table 1). During the sample period, they most likely rented homes, lived with family members, or purchased their homes only after the crisis. To perform a placebo test on these non-homeowners, I assign each of them a pseudo zip code and a pseudo purchase time. The pseudo zip code is imputed using the most common 5-digit physician zip code for every combination of physician tenure (5-year bins), physician gender (male or female), and hospital market (3-digit zip code) within the homeowner sample (i.e., the main analytic sample). The pseudo purchase time is imputed using the median purchase year-quarter for the same combination. I then compute pseudo housing returns for each of these physicians as if they had purchased a home in the pseudo zip code at the pseudo time.

Appendix Table A7 reports the results of this placebo test. The estimates are statistically insignificant, suggesting that non-homeowner physicians do not adjust their C-section rates in response to pseudo housing wealth shocks, providing additional support for the causal interpretation of the main results.

V Additional Results

This Section provides additional results. First, I explore the heterogeneous effects by physician characteristics and patient characteristics in subsection V.A. I then examine the effect on a number of other treatment margins in childbirth in subsection V.B. Finally, I study the impacts of physician behavior on patient health in subsection V.C.

V.A Heterogeneous Effects

To provide a more comprehensive picture on the effect of physicians' financial health on their treatment choices, this section explores heterogeneities along two dimensions: patient characteristics and physician characteristics. These heterogenous effects are summarized graphically in Figures 5 and 6, with full regression results reported in Appendix Tables A8 and A9.

Heterogeneous Effects by Patient Characteristics. The effect of financial health on physician treatment choices can also be unequal for different patients. Understanding this distributional effects is crucial for evaluating the welfare consequences of physician behavior and for designing more targeted policy interventions. I highlight the role of two patient-side factors that have been studied in the healthcare literature: (1) patient race and ethnicity, and (2) expected benefit, or medical appropriateness, of receiving a C-section.

To examine whether the effect varies by patient race and ethnicity, I estimate separate regressions for three groups of patients: non-Hispanic Black, Hispanic, and others. Figure 5(a) shows the corresponding coefficient estimates and 95% confidence intervals. The effect is most statistically significant among non-Hispanic Black patients, with the magnitude more than twice as large as the baseline average effect. Specifically, a one-standard-deviation decrease in physician housing returns is associated with a 4.3 percentage point increase (or 11%) in the C-section rate for non-Hispanic Black patients. While the effects for Hispanic and other patients are of the same sign, they are less precisely estimated.

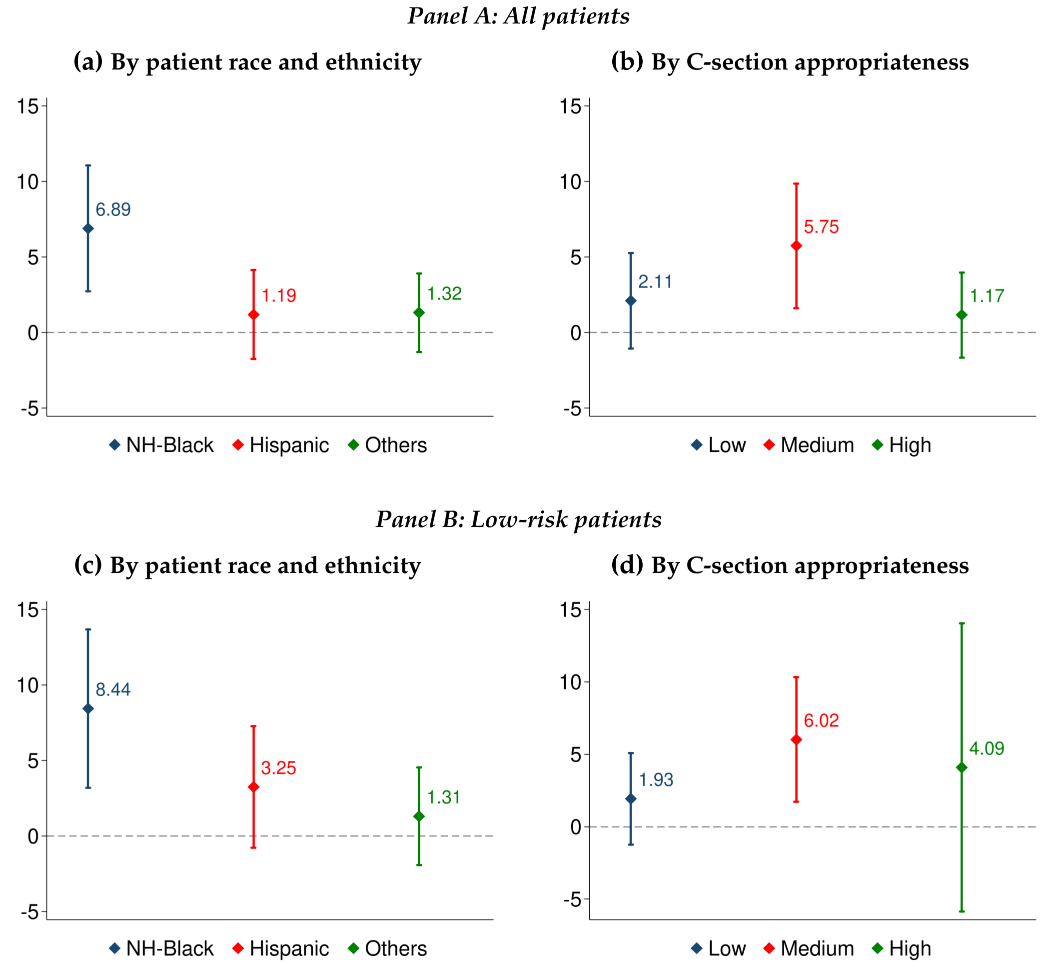
This finding is consistent with a trending literature showing that Black patients are more vulnerable to provider discretion, all else equal. For instance, Singh and Venkataramani (2022) find that Black patients tend to wait longer, receive less care, and ultimately face higher mortality when hospitals approach capacity constraints. In a setting more directly related to childbirth, Corredor-Waldron et al. (2024) document a racial gap in C-section rates between non-Hispanic Black and other patients—a gap that disappears when the cost of unnecessary C-sections increases. My findings add to this growing body of evidence by highlighting how racial disparity in healthcare may widen during periods of deteriorating physician financial health.

How physicians' financial shocks affect patient welfare also depends critically on whether the affected patients are appropriate candidates for C-sections. Intuitively, physicians are likely to have already performed C-sections on patients who stand to benefit the most, and may be less inclined to do so for those with minimal expected benefits even facing greater financial incentives. In other words, patients with *medium*-level expected benefits should be more likely to receive C-sections at the margin. To test this prediction, I first use all patients in the analytic sample and estimate a Logit regression model with a binary indicator for C-section as the outcome and all patient demographics and risk factors as predictors. The predicted value from this model is interpreted as each patient's "appropriateness" for receiving a C-section.[15] This approach follows prior work in assuming that, on average, physicians have performed the "correct" percentage of C-sections in the patient population (Currie and MacLeod, 2017; Robinson et al., 2024).

Figure 5(b) presents the estimates separately for three equal-sized groups of patients, classified by low, medium, and high appropriateness for receiving a C-section. As expected, the effect is strongest among patients in the medium-appropriateness group: the magnitude is more than twice than that of the low-appropriateness group and more than three times that of the high-appropriateness group. It is worth noting that the "appropriateness" measure does not perfectly correlate with the "low-risk" indicator used in sample subsetting (i.e., Panel B in most tables), as the former incorporates a broader set of clinical risk factors beyond those flagged in the low-risk definition. In fact, similar patterns regarding patient race and medical appropriateness remain even when restricting the analysis to low-risk patients, as shown in Figures 5(c) and 5(d).

[15] Appendix Table A1 reports the results from this Logit regression and Appendix Figure A5 shows the distribution of the predicted C-section appropriateness.

Figure 5. Heterogeneous Effects by Patient Characteristics



Notes: These figures show the heterogeneous effects of physician housing returns on C-section rate by patient characteristics, as discussed in Section V.A. Coefficient estimates (numbers alongside the marker) as well as 95% confidence intervals from subsample regressions are reported. Panels A and B report results for all patients and for low-risk patients, respectively. Figures (a) and (c) show the effects by patient race and ethnicity. Figures (b) and (d) show the effects by patients' predicted appropriateness for C-section. Full regression results are reported in Appendix Table A8.

Heterogeneous Effects by Physician Characteristics. The effect of financial health on physician treatment choices may vary across different providers. I focus on the role of three key factors: (1) physician practice styles, (2) physician competition, and (3) physician gender.

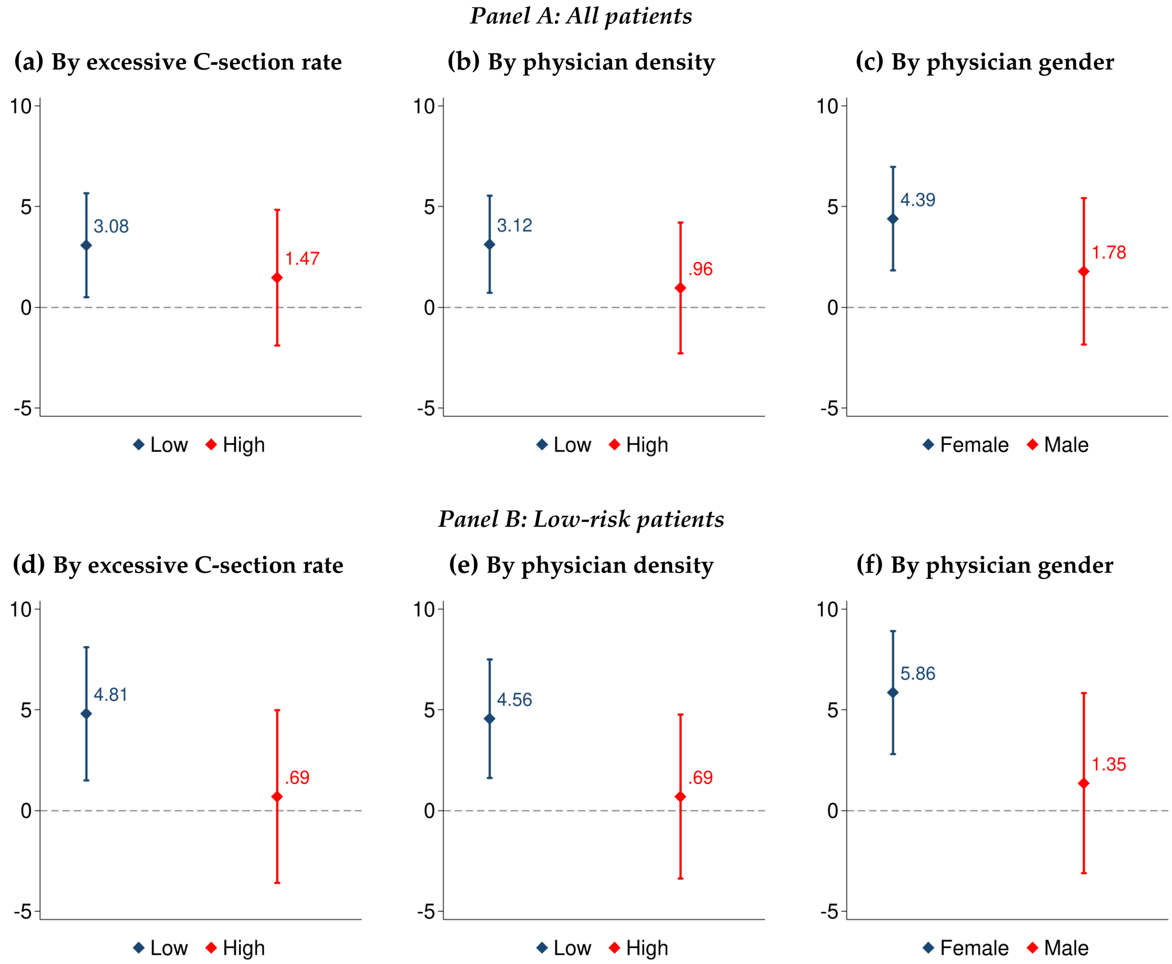
I begin by investigating how physicians' responses depend on their ex ante practice styles. Prior studies have pointed out that physician practice styles are highly persistent (Epstein and Nicholson, 2009), and that physicians' treatment decisions tend to be autocorrelated over time (Jin et al., 2024). It is therefore worth asking whether the observed increase in C-section rates is primarily driven by physicians who were already more likely to perform C-sections before the shock, or by those who were not. I first define a measure of *excessive* C-section rate for each physician, calculated as the difference between their actual C-section rate and their predicted rate prior to the housing shock.[16] Figure 6(a) shows results for two subsamples, divided based on whether the physician's excessive C-section rate is above or below the median. The effect of housing shocks is mainly driven by physicians with a lower ex ante excessive C-section rate. This finding provides evidence that physician practice styles can change over time, and also suggests that C-section rates across different providers may converge during times of negative financial shocks.

Next, I examine whether the estimated effect varies by the landscape of market competition. The direction of this effect is ex ante unclear. On the one hand, competition may place downward pressure on physicians' profits, incentivizing stronger responses to financial shocks; on the other hand, physicians in more competitive markets may have already approached to optimal treatment levels, leaving little room for adjustments even when they are more financially motivated. Following previous literature, I use variation in local physician density as a proxy for competition (Gruber and Owings, 1996; Baicker et al., 2006). Specifically, physician density is defined as the number of OB/GYNs per birth in a county, measured and fixed as of 2006. Patients are then grouped based on whether they reside in lower-density or higher-density physician markets. Figure 6(b) shows that the effect only exists in low-density markets, consistent with the idea that physicians in these areas are more capable of adjusting their practice styles. This finding adds to the literature on how physician competition shapes physician-induced demand by focusing on a scenario where physicians are in poor conditions of personal finance (Dunn and Shapiro, 2018; Brekke et al., 2019; Ikegami et al., 2021).

Lastly, I study if physician gender plays a role in the treatment choices. In my data, 59% of OB/GYNs are female, who deliver about 56% of all births. Existing work has shown that female physicians tend to work less because of more commitments outside of work (Pruckner et al., 2025), and more likely to adopt less aggressive treatment options (Currie et al., 2016). However, since all childbirth patients are female, female physicians also introduce the potential benefits of gender concordance between patient and physician, such as greater empathy and better communication. For example, Cabral and Dillender (2024) and Greenwood et al. (2018) have found that female patients are more likely to receive favorable evaluations and have lower mortality rates from physicians of the same gender. Figure 6(c) shows that patients are more likely to receive C-sections when their female physicians are financially shocked, suggesting that gender concordance probably does not generate overwhelming benefits in this context. That said, it is also important to recognize that female physicians may face greater constraints on working time and may be more sensitive to financial shocks.

[16]Specifically, a predicted C-section probability is estimated for each patient using her demographics and risk factors with a Logit model (Column (1) of Appendix Table A1). I then aggregate the actual C-section indicator and the predicted C-section probability across all patients seen by a given physician, and calculate the difference (i.e., the excessive C-section rate).

Figure 6. Heterogeneous Effects by Physician Characteristics



Notes: These figures show the heterogeneous effects of physician housing returns on C-section rate by physician characteristics, as discussed in Section V.A. Coefficient estimates (numbers alongside the marker) as well as 95% confidence intervals from subsample regressions are reported. Panels A and B report results for all patients and for low-risk patients, respectively. Figures (a) and (d) show the effects by physicians' excessive C-section rate ex ante. Figures (b) and (e) show the effects by physician density in the local market. Figures (c) and (f) show the effects by physician gender. Full regression results are reported in Appendix Table A9.

V.B Effects on Other Treatment Margins

A natural follow-up question is whether physicians adjust their treatment choices along other margins when facing negative financial shocks. I begin by examining differences in physicians' responses between scheduled and unscheduled C-section rates. C-sections can be scheduled before the onset of labor, either at the recommendation of physicians or at the request of patients. Once labor begins, physicians may also recommend a C-section (i.e., unscheduled C-sections) if they believe the benefits of an immediate surgery outweigh the risks of continuing labor. In unscheduled cases, it is typically easier for physicians to persuade patients to undergo a C-section, because the clinical guidelines on when to discontinue labor are less clear, and patients have limited time and information to challenge the physician's judgment. In other words, if the observed effects are primarily driven by physicians' decisions rather than patients' preferences, one should expect stronger effects for unscheduled C-sections than for scheduled ones.

Following Henry et al. (1995); Gregory et al. (2002), I define unscheduled C-sections as those associated with ICD diagnosis codes indicating a trial of labor. In Florida, approximately 77% of all C-sections are scheduled, though not all are maternally requested. Columns (1) and (2) of Table 3 use unscheduled and scheduled C-section rates as the outcome variables, respectively. Physician housing returns significantly predict the incidence of unscheduled C-sections but not scheduled ones. This sharp contrast suggests that the observed increase in C-section rates is not driven by maternal preferences for elective procedures but is instead concentrated among patients who had initially revealed a preference for vaginal delivery. This result is also consistent with Johnson and Rehavi (2016), who show that physician mothers are less likely to receive unscheduled C-sections compared to non-physician mothers.

One might wonder whether the higher C-section rate is a result of physicians using *fewer* assisted methods during attempted vaginal deliveries. One such method is induction, which is used to stimulate uterine contraction and avoid a prolonged first stage of labor. Column (3) of Table 3 reports the results using an indicator for whether a patient received induction as the dependent variable. The estimate is statistically insignificant, indicating that physicians do not appear to reduce medically necessary interventions early in the labor process. Another example of assisted delivery involves the use of vacuum devices or forceps, which are considered ancillary procedures and typically used during the second stage of labor. If physicians are substituting C-sections for these less invasive procedures, one would expect a decline in their usage when physicians face negative financial shocks. However, Column (4) of Table 3 uses an indicator for vacuum/forceps as the outcome variable and finds no evidence for patients less likely to receive such procedures.[17]

There may also be additional treatments not captured by the use of C-sections, induction, or ancillary procedures. For example, patients might receive further tests or services after the labor and delivery process, such as extra monitoring, blood work, or other medical interventions. To examine these broader treatment margins, I follow Johnson and Rehavi (2016) and use the total dollar amount of hospital charges as a summary measure of overall treatment intensity. Column (5) of Table 3 presents the result using logged hospital charges as the dependent variable. Hospital charges significantly increase as physician housing returns decline. Specifically, a one-standard-deviation decrease in physician housing returns leads to a 1.5% increase in hospital charges, equivalent to a $194 increase for the average patient. This effect, however, becomes statistically insignificant once conditioning on delivery mode, suggesting that the observed increase in hospital charges is largely explained by the margin of C-section versus vaginal delivery.[18]

Lastly, I explore the effect on the number of births delivered by each physician over time (i.e., the extensive margin). One might expect that physicians could also respond to negative financial

[17]There is an increased use of vacuum/forceps for vaginal births but not for C-section births (Appendix Table A10).

[18]See Appendix Table A10 for subsample results by delivery mode.

shocks by treating more patients in an effort to compensate for wealth losses. To test this possibility, I regress the number of deliveries on physician housing return using an aggregated data set at the physician×year-quarter level, controlling for physician and year-quarter fixed effects. Column (6) of Table 3 reports the result from a Poisson regression model. The estimate is statistically insignificant, which is perhaps unsurprising given that the number of baby deliveries can be more affected by demand-side factors beyond physicians' control, such as underlying fertility rates.

Table 3. Effects on Other Treatment Margins

Panel A: All patients	*Unscheduled C-section*	*Scheduled C-section*	*Induction*	*Vacuum/Forceps*	*Hosp. charges*	*# Deliveries*
	(1)	(2)	(3)	(4)	(5)	(6)
Physician housing return	1.953	0.426	-0.711	0.907	0.021	-0.042
	(0.628)	(0.884)	(0.848)	(0.509)	(0.009)	(0.060)
Year-quarter FE						✓
Physician FE	✓	✓	✓	✓	✓	✓
Patient covariates	✓	✓	✓	✓	✓	
Hospital×year-quarter FE	✓	✓	✓	✓	✓	
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	
Mean (dep. var.)	9.23	30.96	16.63	5.22	9.35	41.51
Observations	187,873	187,873	187,873	187,873	187,873	5,678

Panel B: Low-risk patients	*Unscheduled C-section*	*Scheduled C-section*	*Induction*	*Vacuum/Forceps*	*Hosp. charges*	*# Deliveries*
	(1)	(2)	(3)	(4)	(5)	(6)
Physician housing return	2.963	0.167	-1.369	0.918	0.021	-0.045
	(0.805)	(0.991)	(1.126)	(0.559)	(0.010)	(0.060)
Year-quarter FE						✓
Physician FE	✓	✓	✓	✓	✓	✓
Patient covariates	✓	✓	✓	✓	✓	
Hospital×year-quarter FE	✓	✓	✓	✓	✓	
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	
Mean (dep. var.)	11.27	11.45	22.15	5.62	9.26	41.78
Observations	133,551	133,551	133,551	133,551	133,551	5,637

Notes: This table reports results from regressions of other treatment margins on physician housing returns. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1)–(4) use binary indicators (scaled by 100) for unscheduled C-section, scheduled C-section, labor induction, and vacuum/forceps use as outcome variables, respectively. Column (5) uses logged hospital charges as the outcome variable. Columns (1)–(5) include patient characteristics and fixed effects as specified in Equation (2). Column (6) presents results from a Poisson regression of physician-level delivery counts, controlling for year-quarter and physician fixed effects. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

V.C Effects on Patient Health

Previous sections have shown that negative shocks to physicians' financial health influence their treatment choices. To assess the potential effect on patient welfare, this section explores whether shifts in physician behavior translate into measurable differences in health outcomes.

Theory offers ambiguous predictions regarding this issue. On the one hand, patient health may worsen if physicians' adoption of more profitable procedures results in overtreatment that deviates from the clinical optimum. On the other hand, financially distressed physicians may practice more conservatively and cautiously to avoid adverse outcomes. In the meanwhile, the patients most affected by these behavioral shifts are likely those who are close to being indifferent between cesarean and vaginal deliveries (i.e., the "marginal" patients). Because the relative benefits and risks of C-sections are less clear for this patient group, whether the increased use of C-sections leads to meaningful changes in health outcomes remains an empirical question.

I focus on two sets of maternal health outcomes in this section. The first set concerns the time a patient stays in the hospital (from the date of admission to the date of discharge). I preserve the baseline specification in Equation (2) and use the natural logarithm of one plus the total length of stay as the dependent variable.[19] Column (1) of Table 4 reports the result: patients' length of stay tends to increase following physician financial shocks. Specifically, a one-standard-deviation decrease in physician housing returns leads to a 0.5% increase in length of stay, or approximately 0.013 days. Although small in magnitude, this estimate aligns with findings from prior research. For example, Card et al. (2023) show that delivering in a high-cesarean-rate hospital leads to a similar-sized increase in patient length of stay.

To explore what drives the increase in length of stay, Columns (2) and (3) of Table 4 decompose the total stay into two components: pre-delivery stay (the number of days from admission to delivery) and post-delivery stay (the number of days from delivery to discharge). For the average patient, the total length of stay is 2.54 days, consisting of 0.29 days pre-delivery and 2.25 days post-delivery. The observed increase in overall length of stay is primarily driven by longer post-delivery stays, which is consistent with more use of C-sections, as these procedures are more invasive and typically require longer recovery times. This pattern also suggests that physicians are not responding by scheduling more C-sections in advance; if that were the case, pre-delivery stays would likely be significantly shorter.

To further understand how physician financial shocks affect the *distribution* of inpatient stays, I define a binary indicator for *prolonged* length of stay. This indicator equals one if the total stay exceeds 4 days for cesarean births or 2 days for vaginal births, and zero otherwise. In the raw data, approximately one-fifth of all patients experience prolonged inpatient stays. Column (4) of Table 4 reports regression results using this indicator as the outcome variable. Conditional on patient characteristics, the probability of prolonged stays significantly decreases as physician housing returns decline. Specifically, a one-standard-deviation decrease in physician housing returns reduces the probability of prolonged stays by about 1 percentage point, or 5% relative to the mean. This finding suggests that although higher C-section rates lead to longer stays on average, some patients may have benefited, possibly by being assigned to more clinically appropriate treatments.

[19]Poisson regressions using the length of stay as a count outcome yield similar results (Appendix Table A11).

Table 4. Effects on Maternal Health Outcomes

Panel A: All patients								
	Length of stay				*Complications*			
	(1) Total	(2) Pre-birth	(3) Post-birth	(4) Prolonged	(5) Hemorrhage	(6) Infection	(7) Laceration	(8) Severe
Physician housing return	0.007	-0.008	0.012	-1.975	-0.104	0.308	0.118	0.020
	(0.005)	(0.008)	(0.004)	(0.855)	(0.260)	(0.226)	(0.398)	(0.195)
Patient covariates	✓	✓	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	1.24	0.19	1.15	19.50	1.40	0.97	2.29	0.62
Observations	187,873	187,873	187,873	187,873	187,873	187,873	187,873	187,873

Panel B: Low-risk patients								
	Length of stay				*Complications*			
	(1) Total	(2) Pre-birth	(3) Post-birth	(4) Prolonged	(5) Hemorrhage	(6) Infection	(7) Laceration	(8) Severe
Physician housing return	0.005	-0.007	0.009	-2.953	-0.449	0.423	0.251	0.109
	(0.006)	(0.011)	(0.005)	(1.230)	(0.307)	(0.323)	(0.593)	(0.196)
Patient covariates	✓	✓	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	1.21	0.22	1.12	23.76	1.39	1.13	3.07	0.42
Observations	133,551	133,551	133,551	133,551	133,551	133,551	133,551	133,551

Notes: This table reports results from patient-level regressions of maternal health outcomes on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1)–(3) use the log of one plus the total length of stay, pre-birth stay, and post-birth stay, respectively, as dependent variables. Columns (4)–(8) use indicators (scaled by 100) for prolonged hospital stay (defined as $\geq$ 4 days for C-sections or $\geq$ 2 days for vaginal deliveries), hemorrhage, infection, laceration, and severe complications, respectively. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Finally, I examine a range of maternal morbidity outcomes, or complications that occur during or shortly after labor and delivery. Following prior studies (Johnson and Rehavi, 2016; Freedman and Hammarlund, 2019; La Forgia, 2022), I define four types of maternal morbidity using ICD codes: hemorrhage, infection, laceration, and severe maternal morbidity. The first two types, hemorrhage and infection, can occur in both cesarean and vaginal deliveries. The third type, laceration, is typically associated only with vaginal births. The fourth type, severe maternal morbidity, is less common and includes serious complications such as sepsis, eclampsia, anesthesia-related issues, and other adverse events that often require additional interventions like hysterectomy or blood transfusion (Callaghan et al., 2012; Kilpatrick et al., 2016). In my sample, over 5% of patients experience at least one of these complications.[20]

As shown in Columns (5) to (8) of Table 4, physician financial shocks do not significantly affect

[20]One potential concern is that the Florida inpatient discharge data may under-report these complications, as morbidity rates appear slightly lower than those reported by Johnson and Rehavi (2016), who use data from California. Another possible outcome, maternal in-hospital mortality, is even more rarely observed in the Florida data, with a rate of approximately 4 per 100,000 women. Given these limitations, one should perhaps interpret the estimated health effect here as a conservative lower bound.

maternal morbidity, at least for the four measures considered. These results, along with those related to length of stay, remain consistent within the low-risk subsample, as reported in Panel B of Table 4. Overall, I find no strong evidence that physicians' responses to negative financial shocks negatively affect maternal health. If anything, higher C-section rates prevent some patients from entering prolonged inpatient stays, but not at a cost of significantly longer length of stay or higher complication rates. That said, it is important to acknowledge that C-sections may impose other forms of hardship to mothers that are not captured by my data, such as long-term reproductive consequences (e.g., repeat C-sections) and mental health issues (e.g., postpartum depression). In addition, I am unable to assess the health impacts on infants due to data limitations.

VI Discussion

Thus far, I have shown that physicians are more likely to perform C-sections in response to negative housing wealth shocks. However, negative wealth shocks can trigger such behavioral responses through multiple possible mechanisms. For example, a decline in wealth may increase physicians' marginal utility of income, motivating them to profit from performing more C-sections. Alternatively, negative wealth shocks may place physicians under financial distress, making them want to recover lost income or avoid future risks. Distinguishing between these mechanisms is crucial for interpreting the results and understanding their policy implications.

In what follows, I first introduce a simple conceptual framework in subsection VI.A to reconcile the finding of increased C-section rates. The framework incorporates two key motives underlying physician decision-making: financial incentives and patient welfare. Guided by the predictions from this conceptual framework, I then present empirical evidence to help differentiate the underlying mechanisms in subsection VI.B.

VI.A Conceptual Framework

As discussed in Section II, physician discretion plays a central role in the clinical context of childbirth. The following conceptual framework thus abstracts away from the "negotiation" between physicians and patients, assuming instead that patients follow their physicians' recommendations. This assumption does not exclude patient interests from the decision-making process. Rather, I adopt the standard approach in the healthcare literature and assume that physician agents are (partially) altruistic, incorporating patient welfare into their utility maximization (McGuire, 2000).[21]

The Physician's Problem. I begin by outlining a physician j's utility from treating a childbirth patient i. The physician's utility consists of two key components: personal earnings from the

[21] Although the physician in this context is an obstetrician/gynecologist, the framework can be extended to other clinical settings where physicians choose among treatment options. For example, cardiologists may decide whether a heart attack patient should receive open-heart surgery (e.g., coronary artery bypass grafting, CABG) or a minimally invasive procedure (e.g., percutaneous coronary intervention, PCI).

physician fee (i.e., financial incentives) and medical benefits to the patient (i.e., physician altruism). Both components depend on the specific treatment chosen by the physician, $k \in \{v, c\}$, where v denotes vaginal delivery and c denotes C-section:

$$\max_{k \in \{v,c\}} : U_{i,j,k} = \underbrace{f_j(\omega_k)}_{\substack{\text{personal earnings} \\ \text{to physician}}} + \underbrace{b_k(X_i)}_{\substack{\text{medical benefits} \\ \text{to patient}}} \tag{3}$$

The first term, $f_j(\omega_k)$, captures the pecuniary utility that physician j derives from providing treatment k, where ω_k represents the cost-adjusted physician fee. As discussed in Section II, C-sections generally provide higher financial rewards than vaginal deliveries (i.e., $\omega_c > \omega_v$).[22] The function $f_j(\cdot)$ is assumed to exhibit diminishing marginal utility: the wealthier the physician, the less additional utility they derive from an extra dollar of income. In other words, $\frac{\partial f_j(\omega_k)}{\partial \omega_k}$ is decreasing in physician wealth.

The second component in Equation (3), $b_k(X_i)$, represents the medical benefit to patient i with characteristics X_i from receiving treatment k. A larger $b_k(X_i)$ indicates that, all else equal, treatment k is more appropriate for the patient, and thus choosing a treatment other than k imposes greater disutility on the physician. This disutility arises from physicians' "internal conscience" and reflects physician altruism.

The Probability of C-section. Physician j makes a discrete choice from the treatment choice set to maximize their utility. A C-section is chosen for patient i if and only if:

$$b_v(X_i) - b_c(X_i) \leq f_j(\omega_c) - f_j(\omega_v) \tag{4}$$

The left-hand side of Equation (4), $b_v(X_i) - b_c(X_i)$, represents the differential medical benefits for patient i to receive a vaginal delivery over a C-section (or the "appropriateness" of vaginal delivery). The right-hand side, $f_j(\omega_c) - f_j(\omega_v)$, captures the difference in physician j's personal earnings between the two procedures. A C-section is chosen when the financial benefit of C-section is large enough to outweigh the medical advantage of vaginal delivery. Assuming that $\mathbf{B}(\cdot)$ is the inverse CDF of $b_v(X_i) - b_c(X_i)$, the probability of patient i receiving a C-section can be written as:

$$p_i = \mathbf{B}\big(f_j(\omega_c) - f_j(\omega_v)\big) \tag{5}$$

The probability of C-section increases when the financial incentives to perform C-section strengthen (i.e., when $f_j(\omega_c) - f_j(\omega_v)$ increases), holding others constant.

[22] This is a parsimonious representation of financial incentives. Other costs and benefits associated with these procedures, such as malpractice risk, opportunity cost, and resource use, are assumed to be embedded in the physician fees. For instance, Medicare's Resource-Based Relative Value Scale adjusts physician fees based on time, skill, effort, practice expenses, and malpractice insurance premiums.

The Role of Physician Financial Shocks. In this framework, physician fees ω_c and ω_v are treated as exogenous parameters. For a given patient (i.e., conditional on patient characteristics X_i), financial shocks, such as exogenous changes in physician housing wealth, can affect the probability of C-section through multiple mechanisms.

The first possible mechanism is the standard wealth effect that operates through the diminishing marginal utility of income. A common representation of $f(\cdot)$ with this property is the constant relative risk aversion (CRRA) utility: $f_j(\omega_k) = \frac{(W_j+\omega_k)^{1-\gamma}}{1-\gamma}$, where W_j is physician j's initial wealth level, and γ is the coefficient of relative risk aversion. It is straightforward to see that $\frac{\partial f_j^2(\omega_k)}{\partial \omega_k \partial W_j} = -\gamma(W_j + \omega_k)^{-\gamma-1} < 0$. That is, as a physician' housing wealth decreases, their marginal utility of income increases, strengthening the incentive to earn additional income from C-sections. A distinctive feature of this mechanism is that it operates in both directions. In other words, a positive shock that increases physician wealth would lower their marginal utility of income, persuading them to perform fewer C-sections.

Another possible mechanism is financial distress. Unlike the wealth effect, this channel is activated only when the physician experiences a loss in personal wealth. If financial health deteriorates past a certain threshold, the physician may become especially motivated to recoup losses due to loss aversion or a desire to reach a reference income level (Rizzo and Zeckhauser, 2003; Goette et al., 2004). At the same time, physicians facing liquidity constraints may be particularly concerned about broader consequences beyond the loss of wealth, such as the costs of loan default, mortgage foreclosure, or even personal bankruptcy (Bernstein, 2021; Dimmock et al., 2021; McCartney, 2021). As a result, they may be more inclined to resort to the more lucrative treatment.

VI.B Distinguishing the Mechanisms

As discussed in the previous subsection, the mechanism of financial distress is muted when the physician's wealth increases, whereas the wealth effect is always in play no matter under positive or negative wealth shocks. In what follows, I first provide evidence that physicians are insensitive to positive wealth shocks. The lack of a symmetric response rules out the possibility that the wealth effect plays a major role in explaining the increase in C-section rate. I then show that effects are stronger for physicians with higher leverages and more limited financial capacities—evidence consistent with fear of real financial stakes causing physician distress.

Asymmetric Responses. Recall that the main analysis focuses on a sample period from 2007 to 2009, during which the Great Recession quickly unfolded and caused a significant decline in housing prices. In contrast, Table 5 reports results for two alternative sample periods when property values were increasing. I first extend the time frame forward and repeat the analysis using data from three pre-crisis years (2004–2006). During this period, nearly all zip codes experienced an increase in property prices. As illustrated in Figure 2, the average physician housing return rose from below 25% at the beginning of 2004 to approximately 90% by the end of 2006. Columns (1) to (3) of Table 5 report regression results based on this alternative sample period, preserving all specifications from Equation (2). Across the board—whether for overall, unscheduled, or scheduled C-section rates–estimates are small in magnitude and statistically insignificant.

Table 5. Effects of Positive Wealth Shocks

Panel A: All patients						
	Sample period: 2004–2006			*Sample period: 2013–2015*		
	(1) C-section	(2) Unscheduled C-section	(3) Scheduled C-section	(4) C-section	(5) Unscheduled C-section	(6) Scheduled C-section
Physician housing return	0.697	0.385	0.312	0.902	2.292	-1.390
	(1.075)	(0.808)	(0.900)	(3.152)	(2.516)	(2.546)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	37.55	9.32	28.24	41.04	8.02	33.02
Observations	193,784	193,784	193,784	121,911	121,911	121,911

Panel B: Low-risk patients						
	Sample period: 2004–2006			*Sample period: 2013–2015*		
	(1) C-section	(2) Unscheduled C-section	(3) Scheduled C-section	(4) C-section	(5) Unscheduled C-section	(6) Scheduled C-section
Physician housing return	0.731	0.198	0.533	-0.251	1.570	-1.821
	(1.300)	(0.985)	(1.010)	(4.406)	(3.118)	(3.189)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	21.48	10.90	10.57	21.25	9.87	11.38
Observations	141,533	141,533	141,533	84,776	84,776	84,776

Notes: This table reports results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The C-section indicator is scaled by 100. All regressions include patient characteristics and fixed effects as in the baseline specification. Columns (1)–(3) use data from 2004-Q1 to 2006-Q4; Columns (4)–(6) use data from 2013-Q1 to 2015-Q3. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

I also examine a post-crisis recovery period when house prices began to rebound. In the data, most physicians started to experience positive housing returns since around 2013. This trend aligns with the Federal Housing Finance Agency (FHFA) House Price Index which shows that Florida's house values hit post-crisis low in mid-2012 and recovered ever since, nearly returning to pre-crisis peak by the end of 2018 (FRED, 2018). Columns (4) to (6) of Table 5 report results for the 2013–2015 period.[23] Once again, the estimates are statistically insignificant. These null results also hold in the subsample of low-risk births, as shown in Panel B of Table 5. Taken together, these findings suggest that physicians do not reduce their use of C-sections in response to positive

[23]The Florida data used in this study end in 2015-Q3. However, there is no clear reason to expect physician responses to differ after 2015. Results for the 2010–2012 period are consistent with the main findings.

housing shocks, supporting the argument that the wealth effect being less relevant in driving physician behavior.

A growing literature similarly finds that households tend to respond more strongly to negative real estate shocks than to positive ones (Bernstein, 2021; Bernstein et al., 2021; Aslan, 2022). The asymmetric nature of physicians' responses may help explain why C-section rates remained stubbornly high even after the crisis. At face value, this result can also be explained by the behavioral theory of loss aversion (Tversky and Kahneman, 1991; Genesove and Mayer, 2001), which posits that individuals weigh losses more than equivalent gains. While I cannot rule out this possibility, the evidence in the following subsection points instead to the role of real financial stakes, with physician behavior changing across the threshold of liquidity constraints.

Physicians' Loan-To-Value Ratios. Physicians with greater debt are more economically vulnerable and thus more likely to experience financial distress. It is harder for these physicians to manage cash flows, borrow against home equity, or expand their business, among other activities. C-sections may become especially attractive in such circumstances, as they offer higher payments and therefore greater liquidity.[24] I therefore hypothesize that the effect of negative housing shocks is more pronounced among physicians who are close to negative housing equity.

To measure a physician's housing equity, I impute their current Loan-To-Value (LTV) ratio for each property, defined as the loan balance divided by the market value. The loan balance is amortized to the current period based on the original mortgage amount, term, and interest rate at the time of origination. The market value is estimated as the purchase price multiplied by the cumulative housing return for the corresponding zip code. As of the first quarter of 2007, the median physician has an LTV ratio of about 36%, with the 25th percentile at 12% and the 75th percentile at 85%.

Following Bernstein et al. (2021) and Dimmock et al. (2021), I define a physician as deeply in debt if their current LTV ratio is greater than or equal to 90%.[25] Columns (1) to (3) of Table 6 present results using a subsample of patients whose physicians have high LTV ratios. As in the main analysis, negative housing shocks significantly predict higher average and unscheduled C-section rates, but not the scheduled C-section rate. The magnitudes of the estimates are roughly three times larger than those in Table 2. Columns (4) to (6) show results for physicians with safer LTV ratios (i.e., below 90%). These estimates are smaller and statistically weaker, with significant effects only for unscheduled C-sections. Taken together, these results lend support for liquidity constraints or fear of default being important in shaping physician behavior.

[24] C-sections may also serve as a form of defensive medicine for financially distressed physicians who are less able to bear the risks of malpractice lawsuits, reputational damage, or job loss.

[25] One may worry that highly leveraged physicians could be exposed to disproportionally larger shocks. However, Appendix Figure A6 shows the distribution of (demeaned) housing returns for physicians with high LTVs is not significantly on the right of that for physicians with low LTVs.

Table 6. Effects by Physician Loan-To-Value Ratios

Panel A: All patients						
	Physicians LTV: ≥ 90%			*Physicians LTV: < 90%*		
	(1) C-section	(2) Unscheduled C-section	(3) Scheduled C-section	(4) C-section	(5) Unscheduled C-section	(6) Scheduled C-section
Physician housing return	8.428	7.008	1.420	0.893	2.000	-1.108
	(3.946)	(3.665)	(3.997)	(1.177)	(0.737)	(1.054)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital-year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code-year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	41.26	9.36	31.90	39.78	9.20	30.58
Observations	50,139	50,139	50,139	137,734	137,734	137,734

Panel B: Low-risk patients						
	Physicians LTV: ≥ 90%			*Physicians LTV: < 90%*		
	(1) C-section	(2) Unscheduled C-section	(3) Scheduled C-section	(4) C-section	(5) Unscheduled C-section	(6) Scheduled C-section
Physician housing return	13.488	8.819	4.669	1.706	3.245	-1.539
	(5.622)	(4.860)	(4.382)	(1.553)	(0.989)	(1.137)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital-year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code-year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	23.56	11.44	12.12	22.41	11.22	11.19
Observations	35,413	35,413	35,413	98,138	98,138	98,138

Notes: This table reports results from subsample regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The C-section indicator is scaled by 100. Columns (1)–(3) include patients whose physicians have an Loan-To-Value (LTV) ratio greater than or equal to 90%; Columns (4)–(6) include those with an LTV ratio smaller than 90%. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

To summarize, the asymmetric responses to positive and negative shocks, along with the stronger effects among highly leveraged physicians, suggest that financial distress is a primary mechanism through which physicians' financial health influences their treatment decisions. Admittedly, other factors—such as psychological stress (Currie and Tekin, 2015; Engelberg and Parsons, 2016)—may correlate with or even amplify the effects of financial distress. These findings do not entirely rule out the wealth effect either, although back-of-the-envelope calculations imply that physicians were unlikely to fully offset their wealth losses.[26]

[26]Combining the average number of deliveries per physician from Table 1 and the coefficient in Column (3) of Table 2, I estimate that a physician would perform approximately two additional C-sections per year, resulting in about $1000 in extra income. This amount accounts for only a small portion of their wealth losses but indeed aligns with the findings in Gruber and Owings (1996).

VII Conclusion

This paper examines how physicians' financial health influences their treatment decisions and patient health outcomes. I leverage a novel data set that links physicians' real estate holdings to their clinical behavior and exploit within-physician variation in housing returns induced by the Great Recession. In the context of childbirth, I find that physicians increase their use of C-sections in response to negative housing wealth shocks. Physicians' responses are concentrated in the delivery mode, rather than through changes in other treatment margins or overall workload. Importantly, I find no decisive evidence that patient health outcomes are substantially worse off, although non-Hispanic Black patients and those with moderate expected benefits from C-sections are most susceptible to shifts in physician behavior.

I interpret these findings through a conceptual framework that incorporates financial incentives and patient welfare as key drivers of physician decision-making. The framework allows me to discuss mechanisms through which negative financial shocks may encourage more C-sections, such as the wealth effect and the financial distress channel. Empirical evidence points to financial distress as the dominant mechanism, as physicians do not respond to positive wealth shocks, but respond more strongly when in greater liquidity constraints.

These findings carry several policy implications. First, they underscore the importance of policies that integrate financial literacy into medical education, as well as federal programs aimed at improving physicians' financial resilience, such as the Public Service Loan Forgiveness program and the Income-Driven Repayment plan. Notably, federal student loan programs are expected to be scaled back by 2026 under the One Big Beautiful Bill Act, raising concerns about provider vulnerability during future economic downturns. The results in this paper suggest that these programs are crucial for maintaining healthcare delivery as they help prevent physicians from sliding into financial distress.

The limited evidence for a standard wealth effect also aligns with prior research which documents that the income effect is relatively small and dominated by the substitution effect in physician behavior when physician fees change. Finally, this paper sheds light on how financial market frictions can spill over to clinical decision-making. While this paper focus on housing wealth shocks, real estate is not the only source of financial risks. Other risks, such as stock market volatility and student loan repayment, may also affect physicians' behavior. Exploring these broader links between household finance and professional conduct represents an important direction for future research.

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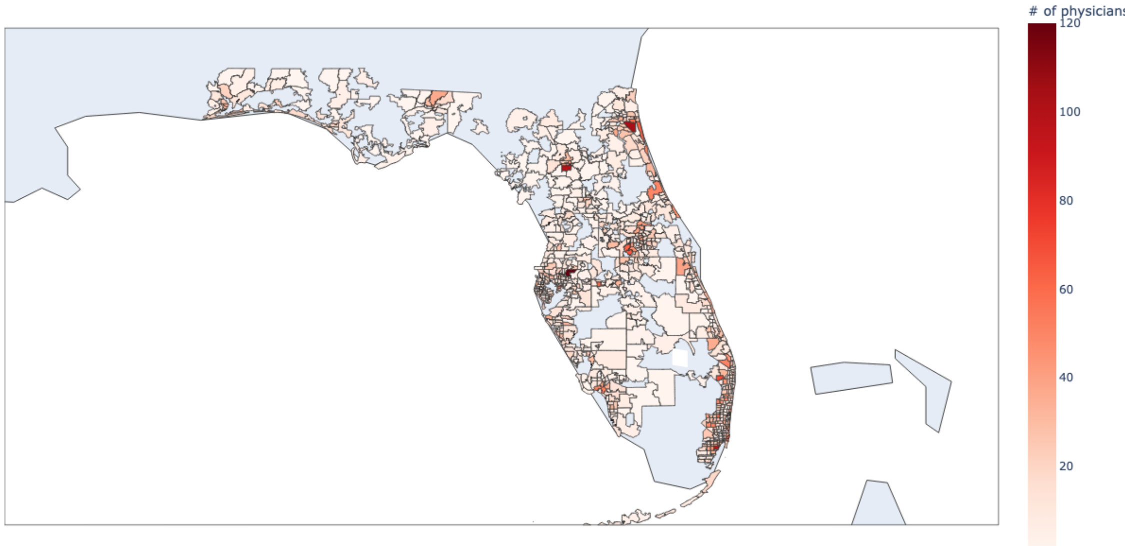
Appendix

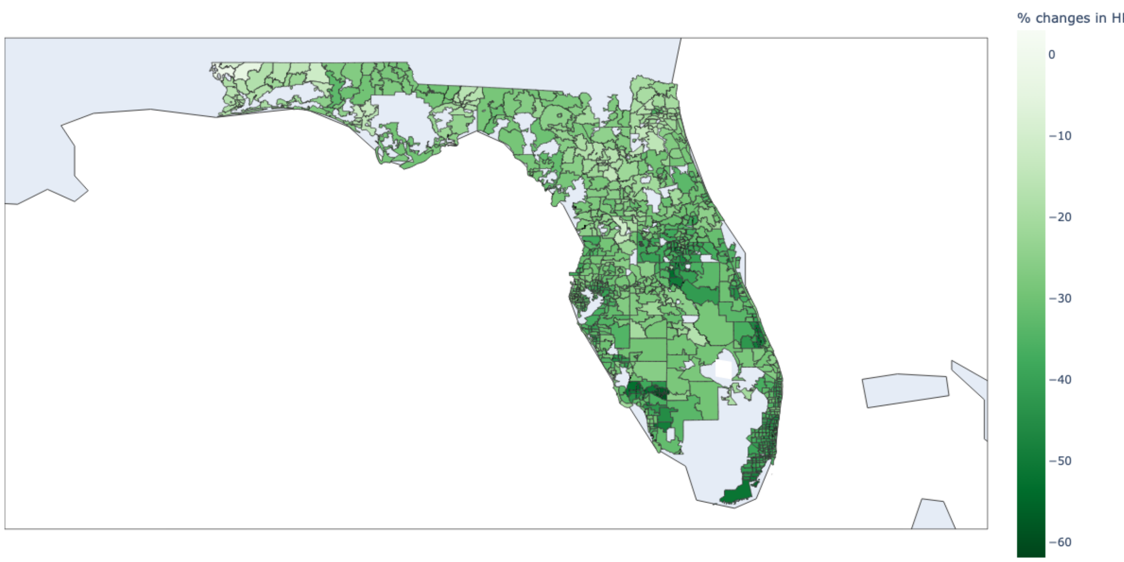
A Additional Figures and Tables

Figure A1. Number of Physicians by Zip Code



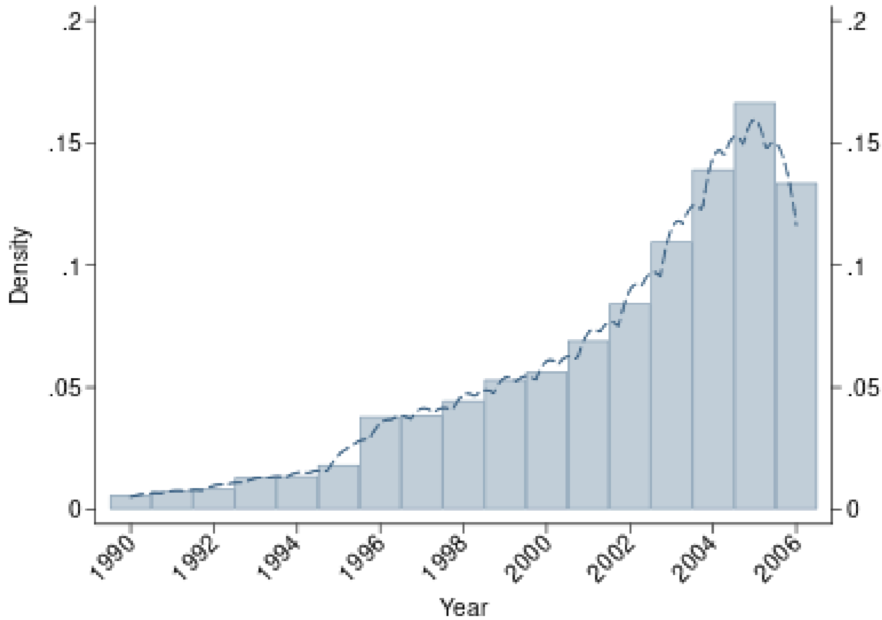
Notes: This figure shows the number of physicians residing in each Florida zip code. Physicians' residences are identified following the procedures described in Appendix B. Only physicians who own a house by the end of 2006 are included (i.e., excluding those with homes sold before or purchased after 2006). Zip codes with missing data of Zillow House Value Index (ZHVI) are excluded.

Figure A2. Changes in housing values by Zip Code



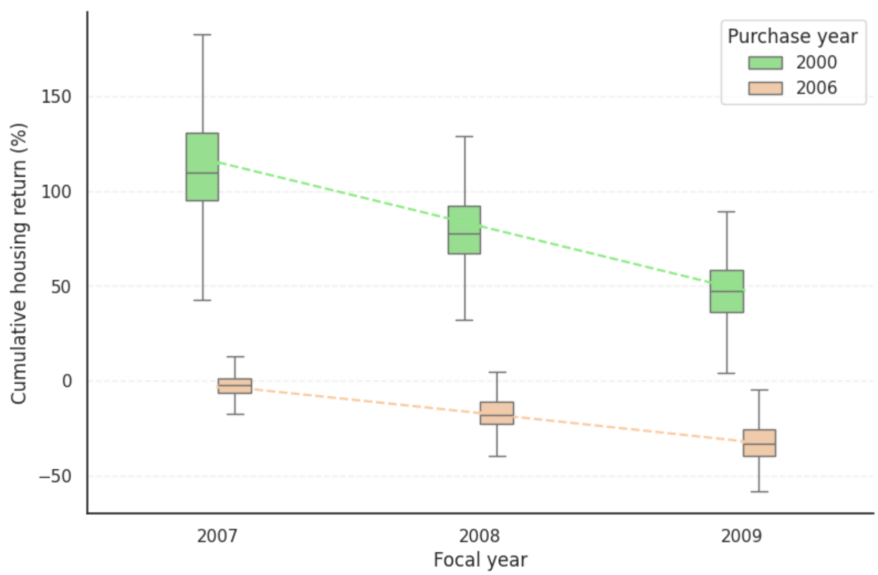
Notes: This figure displays the percentage change in the Zillow Home Value Index (ZHVI) for each Florida zip code from 2007 to 2009. Zip codes with missing ZHVI data are excluded.

Figure A3. **Fractions of Physicians by Purchase Year**



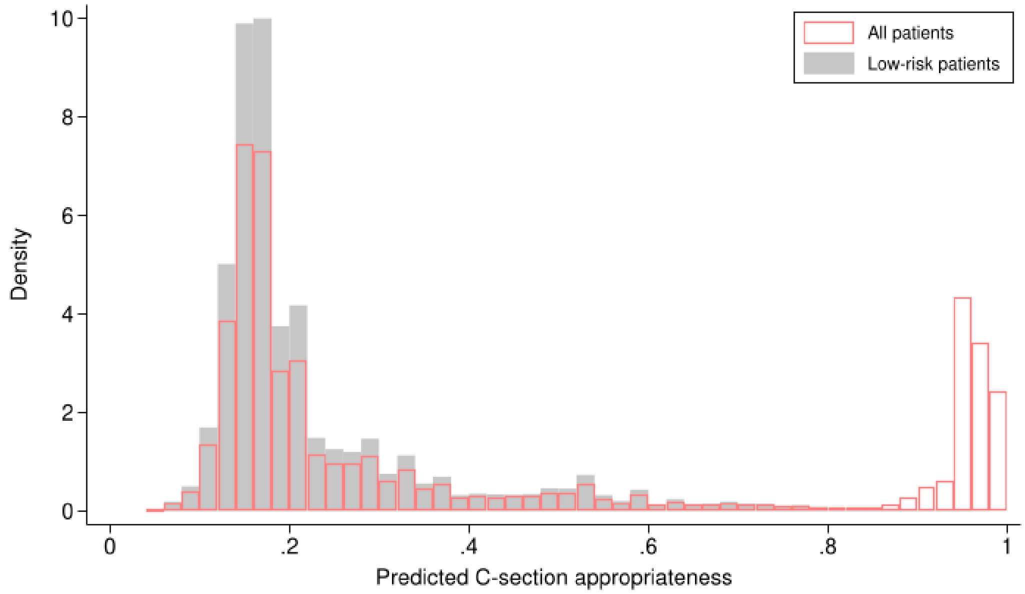
Notes: This histogram shows the fraction of physicians purchasing their homes in various years. Physicians' residences are identified as described in Appendix B. The sample excludes purchases before 1990 or after 2006. The dashed line represents the kernel density.

Figure A4. **Cumulative Returns by Purchase Year**



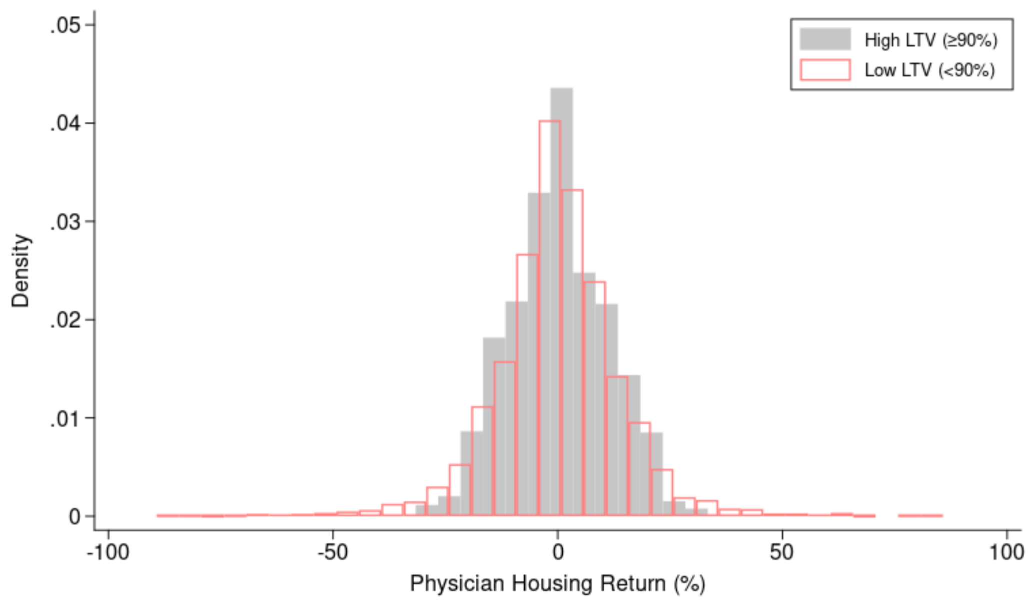
Notes: This boxplot shows the distribution of simulated cumulative housing returns in each year from 2007 to 2009, for physicians residing in different Florida zip codes, assuming house purchases in 2000 and 2006, respectively. Returns are calculated based on the Zillow Home Value Index (ZHVI) over 2007–2009. Zip codes with missing ZHVI data are excluded.

Figure A5. Predicted C-section Appropriateness



Notes: This boxplot shows the distribution of predicted C-section appropriateness for all births and low-risk births, respectively. C-section appropriateness is predicted using a Logit regression model with a binary indicator for C-section as the outcome and all patient demographics and risk factors as predictors. See Section V.A for more discussions and Appendix Table A1 for full regression results.

Figure A6. Distribution of Physician Housing Returns (by LTV)



Notes: This boxplot shows the distribution of physicians' housing returns for physicians with high and low Loan-To-Value ratios, respectively. Housing returns are calculated as in Equation (1) and residualized against physician and year-quarter fixed effects. Loan-To-Value ratios greater than or equal to (smaller than) 90% are defined as high (low). See Section VI.B for more discussions.

Table A1. Nonlinear Probability Model (Logit Model)

	All patients		*Low-risk patients*	
	(1)	(2)	(3)	(4)
Logit models:				
Physician housing return		0.157		0.169
		(0.064)		(0.067)
Black	-0.026	-0.074	0.034	-0.025
	(0.039)	(0.024)	(0.038)	(0.025)
Hispanic	0.237	-0.025	0.235	-0.030
	(0.048)	(0.023)	(0.049)	(0.024)
Weekend delivery	-0.252	-0.214	-0.212	-0.170
	(0.028)	(0.021)	(0.027)	(0.022)
Medicaid	0.163	0.140	0.125	0.108
	(0.038)	(0.028)	(0.040)	(0.030)
Commercial	0.317	0.279	0.260	0.246
	(0.044)	(0.030)	(0.043)	(0.032)
Prior C-section	4.638	4.813	0.000	0.000
	(0.074)	(0.073)	(.)	(.)
35 years of age or older	0.216	0.164	0.246	0.198
	(0.020)	(0.019)	(0.022)	(0.021)
Hypertension	0.833	0.950	0.769	0.869
	(0.030)	(0.026)	(0.031)	(0.028)
Infectious and parasitic conditions	0.741	0.877	0.819	0.935
	(0.057)	(0.054)	(0.055)	(0.055)
Smoking, and alcohol or drug dependence	-0.110	0.076	-0.093	0.075
	(0.039)	(0.029)	(0.041)	(0.031)
Diabetes	0.393	0.487	0.418	0.511
	(0.032)	(0.029)	(0.034)	(0.031)
Heart diseases	0.145	0.171	0.123	0.149
	(0.064)	(0.061)	(0.068)	(0.066)
Antepartum fetal distress	1.803	1.996	1.798	1.974
	(0.140)	(0.123)	(0.138)	(0.127)
Obesity	0.717	0.850	0.751	0.881
	(0.048)	(0.048)	(0.051)	(0.050)
Anemia	0.409	0.531	0.407	0.535
	(0.042)	(0.039)	(0.044)	(0.041)
Malnutrition or insufficient prenatal care	-0.544	-0.462	-0.491	-0.411
	(0.051)	(0.049)	(0.053)	(0.052)
Fetal abnormality	0.295	0.464	0.416	0.560
	(0.093)	(0.070)	(0.087)	(0.069)
Polyhydramnios or oligohydramnios	0.655	0.734	0.660	0.743
	(0.051)	(0.043)	(0.054)	(0.047)
Asthma	-0.025	0.069	-0.045	0.039
	(0.048)	(0.045)	(0.051)	(0.048)
Isoimmunization	-0.167	-0.100	-0.178	-0.117
	(0.050)	(0.046)	(0.056)	(0.053)
Infant size issues	1.682	1.750	1.725	1.805
	(0.056)	(0.053)	(0.059)	(0.054)
Premature rupture of the amniotic sac	0.193	0.256	0.330	0.386
	(0.050)	(0.048)	(0.052)	(0.050)
Twins or more	1.508	1.602	3.011	2.849
	(0.077)	(0.079)	(1.063)	(1.088)
Malposition or malpresentation of fetus	3.825	3.994	0.000	0.000
	(0.073)	(0.074)	(.)	(.)
Preterm	-0.073	-0.061	0.718	0.756
	(0.033)	(0.031)	(1.018)	(1.001)
Other complications of pregnancy	0.079	0.220	0.144	0.271
	(0.063)	(0.066)	(0.069)	(0.071)
Blood disorders or issues	1.487	1.552	1.565	1.628
	(0.053)	(0.056)	(0.062)	(0.065)
Uterine size issues	0.510	0.514	0.452	0.449
	(0.051)	(0.051)	(0.053)	(0.052)
Physical abnormalities	0.779	0.895	0.830	0.933
	(0.042)	(0.037)	(0.043)	(0.039)
Year-quarter FE		✓		✓
Physician FE		✓		✓
Hospital FE		✓		✓
Observations	187,873	187,873	133,551	133,551

Notes: This table reports estimates from Logit regressions using patient-level data from 2007 to 2009. The outcome variable is a binary indicator for C-section (scaled by 100). Regressors include patient covariates such as demographics, insurance type, weekend delivery, and clinical risk factors. Columns (2) and (4) additionally include physician housing returns and fixed effects at physician, hospital, and year-quarter levels. Columns (1) and (2) include all patients; Columns (3) and (4) restricts the sample to low-risk patients. Standard errors, clustered at the physician level, are reported in parentheses.

Table A2. The Role of Patient Risks

	Aggregate risk indicators					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low-risk	Predicted C-section risk	Low-risk	Predicted C-section risk	Low-risk	Predicted C-section risk
Physician housing return	-0.006	-0.001				
	(0.011)	(0.009)				
More affected zip code			-0.004	0.007		
			(0.007)	(0.006)		
Early buyer					0.002	-0.000
					(0.005)	(0.004)
Physician FE	✓	✓				
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	0.71	0.41	0.71	0.41	0.71	0.41
Observations	187,873	187,873	187,873	187,873	187,873	187,873

Notes: This table reports results from patient-level regressions of aggregate risk indicators on physician housing returns, estimated using a linear probability model. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Both aggregate risk indicators are scaled by 100. Columns (1), (3), and (5) use a binary indicator for low-risk status. According to AHRQ, low-risk patients are defined as those without indications of prior C-section, hysterotomy, abnormal presentation, preterm delivery, fetal death, multiple gestation diagnoses, or breech birth. Columns (2), (4), and (6) use the predicted C-section probability from a Logit mode with an actual C-section dummy as the outcome and patient characteristics as predictors. Columns (1) and (2) use physician housing returns as specified in Equation (1). Columns (3) and (4) use a binary dummy for physicians living in more affected zip codes (i.e., whose changes in ZHVI from 2007 to 2009 greater than the median). Columns (5) and (6) use a binary dummy for physicians who purchased their home early (i.e., before the median purchasing year). Columns (1) and (2) include patient characteristics and fixed effects as in the baseline specification. Columns (3)–(6) exclude physician fixed effects as they absorb dummies for physicians in more affected zip codes and early buyers. Standard errors, clustered at the physician level, are reported in parentheses.

Table A3. Extended Fixed Effects to Rule Out Other Selection Channels

Panel A: All patients						
	Patient-hospital matching		*Patient-physician matching*		*Physician-hospital matching*	
	(1) Patients close to hosptial	(2) Patient zip code -hospital FE	(3) Patients far away from physician	(4) Patient zip code -physician FE	(5) Single-homing physicians	(6) Physician-hospital FE
Physician housing return	2.914	2.452	3.427	2.055	2.260	2.493
	(1.194)	(1.030)	(1.664)	(1.053)	(1.372)	(1.044)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	39.98	40.18	40.49	40.18	40.18	40.18
Observations	116,861	187,873	78,149	187,873	100,249	187,873

Panel B: Low-risk patients						
	Patient-hospital matching		*Patient-physician matching*		*Physician-hospital matching*	
	(1) Patients close to hosptial	(2) Patient zip code -hospital FE	(3) Patients far away from physician	(4) Patient zip code -physician FE	(5) Single-homing physicians	(6) Physician-hospital FE
Physician housing return	3.817	3.429	4.306	3.168	3.451	3.369
	(1.439)	(1.291)	(2.345)	(1.294)	(1.776)	(1.270)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	22.97	22.71	22.85	22.71	22.71	22.71
Observations	83,715	133,551	54,821	133,551	70,771	133,551

Notes: This table presents results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since the time of purchase and are reversed in sign. The C-section indicator is scaled by 100. Column (1) restricts the sample to patients whose residential zip code is within 10 miles of their hospital's zip code. Column (2) adds patient zip code×hospital fixed effects. Column (3) restricts the sample to patients whose 3-digit zip code differs from that of their physician. Column (4) adds patient zip code×physician fixed effects. Column (5) limits the sample to physicians practicing at a single hospital during the sample period. Column (6) adds physician×hospital fixed effects. All columns include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A4. Time-Varying Effects of Physician Characteristics

Panel A: All patients

	C-section			
	(1)	(2)	(3)	(4)
Physician housing return	2.510	2.384	2.096	2.403
	(1.065)	(1.023)	(1.074)	(1.021)
Log(physician tenure)	✓			
Exp(physician tenure)		✓		
Physician tenure×year-quarter FE			✓	
Physician gender×year-quarter FE				✓
Patient covariates	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓
Mean (dep. var.)	40.19	40.19	40.19	40.19
Observations	187,873	187,873	187,873	187,873

Panel B: Low-risk patients

	C-section			
	(1)	(2)	(3)	(4)
Physician housing return	3.228	3.132	2.806	3.145
	(1.311)	(1.253)	(1.309)	(1.255)
Log(physician tenure)	✓			
Exp(physician tenure)		✓		
Physician tenure×year-quarter FE			✓	
Physician gender×year-quarter FE				✓
Patient covariates	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓
Mean (dep. var.)	22.72	22.72	22.72	22.72
Observations	133,551	133,551	133,551	133,551

Notes: This table reports results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The C-section indicator is scaled by 100. Compared to the baseline specification, Columns (1)–(4) additionally includes the logarithm of physician tenure, the exponential of physician tenure, physician tenure×year-quarter fixed effects, and physician gender×year-quarter fixed effects. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A5. Alternative Measures of Real Estate Shocks

Panel A: All patients

	C-section			
	(1)	(2)	(3)	(4)
Cumulative return lagged one quarter	2.218			
	(1.029)			
Quarter-over-quarter return		16.130		
		(9.353)		
Year-over-year return			5.766	
			(3.783)	
Log(estimated house price)				-1.745
				(0.814)
Patient covariates	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓
Mean (dep. var.)	40.19	40.19	40.19	40.19
Observations	187,873	187,873	187,873	187,873

Panel B: Low-risk patients

	C-section			
	(1)	(2)	(3)	(4)
Cumulative return lagged one quarter	2.968			
	(1.247)			
Quarter-over-quarter return		19.373		
		(12.566)		
Year-over-year return			8.316	
			(4.911)	
Log(estimated house price)				-3.000
				(1.090)
Patient covariates	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓
Mean (dep. var.)	22.72	22.72	22.72	22.72
Observations	133,551	133,551	133,551	133,551

Notes: This table presents results from patient-level regressions of the C-section indicator on alternative measures of physician real estate shocks, estimated using a linear probability model. The sample spans 2007 to 2009. The C-section indicator is scaled by 100. For real estate shock, Column (1) uses the cumulative return lagged one quarter; Column (2) uses the return over the most recent quarter; and Column (3) uses the return over the past year. All return measures are reversed in sign. Column (4) uses the (logged) level of house prices, computed as the inflation-adjusted purchase price multiplied by the cumulative housing return. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A6. Alternative Sample and Model Specifications

Panel A: All patients					
	Alternative sample specifications		*Alternative clustering of standard erros*		
	(1) Allow physicians' entries/exits	(2) Allow time-varying house porfolios	(3) Cluster at hospital	(4) Cluster at patient zip code	(5) Cluster at physician zip code
Physician housing return	2.532	2.267	2.379	2.379	2.379
	(1.027)	(0.854)	(1.102)	(0.950)	(1.021)
Patient covariates	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓
Mean (dep. var.)	39.97	40.21	40.19	40.19	40.19
Observations	193,202	184,331	187,873	187,873	187,873

Panel B: Low-risk patients					
	Alternative sample specifications		*Alternative clustering of standard erros*		
	(1) Allow physicians' entries/exits	(2) Allow time-varying house porfolios	(3) Cluster at hospital	(4) Cluster at patient zip code	(5) Cluster at physician zip code
Physician housing return	3.359	3.186	3.130	3.130	3.130
	(1.266)	(1.023)	(1.326)	(1.223)	(1.295)
Patient covariates	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓
Mean (dep. var.)	22.59	22.74	22.72	22.72	22.72
Observations	137,467	131,040	133,551	133,551	133,551

Notes: This table reports results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The C-section indicator is scaled by 100. Column (1) includes physicians who entered the labor force after the recession began (i.e., late entries) as well as those who retired before the recession ended (i.e., early exits). Column (2) allows physicians' house holdings to be time-varying and track their housing returns over time. Columns (3)–(5) cluster standard errors at the levels of hospital, patient zip code, and physician zip code, respectively. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively.

Table A7. Placebo Test: Effects on Non-Homeowner Physicians

Panel A: All patients

	C-section		
	(1) All	(2) Unscheduled	(3) Scheduled
Pseudo housing return	0.639	0.198	0.441
	(0.571)	(0.417)	(0.570)
Patient covariates	✓	✓	✓
Physician FE	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓
Mean (dep. var.)	41.10	9.52	31.58
Observations	136,691	136,691	136,691

Panel B: Low-risk patients

	C-section		
	(1) All	(2) Unscheduled	(3) Scheduled
Pseudo housing return	-0.433	0.442	-0.874
	(0.700)	(0.631)	(0.633)
Patient covariates	✓	✓	✓
Physician FE	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓
Mean (dep. var.)	23.44	11.52	11.92
Observations	96,799	96,799	96,799

Notes: This table reports results from a placebo test using a sample of patients treated by non-homeowner physicians. Columns (1)–(3) estimate a linear probability model, using indicators (scaled by 100) for any C-section, unscheduled C-section, and scheduled C-section, respectively, as dependent variables. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The sample spans 2007 to 2009. Non-homeowner physicians are those not matched with any real estate transaction records in CoreLogic. I assign the most common 5-digit physician zip code and the median purchase year-quarter for every combination of physician tenure (in 5-year bins), physician gender (male or female), and hospital market (3-digit zip code) within the homeowner sample, as the pseudo zip code and pseudo purchase time for non-homeowner physicians. See more discussions in Section IV.B. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A8. Heterogeneous Effects by Patient Characteristics

Panel A: All patients								
	Patient race and ethnicity				*Appropriateness of C-section*			
	(1) NH Black	(2) Hispanic	(3) Others	(4) All	(5) Low	(6) Medium	(7) High	(8) All
Physician housing return	6.894	1.193	1.318	1.318	2.109	5.746	1.166	2.109
	(2.124)	(1.498)	(1.324)	(1.336)	(1.613)	(2.103)	(1.436)	(1.623)
Physician housing return×Non-Hispanic Black patient				5.576				
				(2.484)				
Physician housing return×Hispanic patient				-0.125				
				(1.987)				
Physician housing return×Medium appropriateness								3.638
								(2.642)
Physician housing return×High appropriateness								-0.943
								(2.166)
Patient covariates	✓	✓	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	39.18	44.33	39.27	40.20	13.73	24.38	83.83	40.19
Observations	39,860	36,201	111,812	187,873	70,331	54,960	62,582	187,873

Panel B: Low-risk patients								
	Patient race and ethnicity				*Appropriateness of C-section*			
	(1) NH Black	(2) Hispanic	(3) Others	(4) All	(5) Low	(6) Medium	(7) High	(8) All
Physician housing return	8.441	3.247	1.312	1.312	1.926	6.018	4.093	1.926
	(2.674)	(2.051)	(1.647)	(1.664)	(1.618)	(2.192)	(5.078)	(1.648)
Physician housing return×Non-Hispanic Black patient				7.129				
				(3.110)				
Physician housing return×Hispanic patient				1.935				
				(2.606)				
Physician housing return×Medium appropriateness								4.092
								(2.748)
Physician housing return×High appropriateness								2.167
								(4.794)
Patient covariates	✓	✓	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	22.42	25.57	22.06	22.76	13.87	23.98	54.99	22.12
Observations	27,576	24,959	81,016	133,551	66,048	51,483	16,020	133,551

Notes: This table reports results from subsample regressions of the C-section indicator on physician housing returns, estimated using a linear probability model. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The C-section indicator is scaled by 100. Columns (1)–(3) divide the sample by patient race and ethnicity; Column (4) includes interaction terms between physician housing returns and indicators for patient race/ethnicity. Columns (5)–(7) divide the sample by patients' medical appropriateness of receiving a C-section; Column (8) includes interaction terms between physician housing returns and indicators for different levels of C-section appropriateness. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A9. Heterogeneous Effects by Physician Characteristics

Panel A: All patients	*C-section rate ex ante*			*Physician density*			*Physician gender*		
	(1) Low	(2) High	(3) All	(4) Low	(5) High	(6) All	(7) Female	(8) Male	(9) All
Physician housing return	3.083	1.470	1.470	3.123	0.959	0.959	4.395	1.775	1.775
	(1.321)	(1.717)	(1.716)	(1.231)	(1.654)	(1.633)	(1.312)	(1.856)	(1.842)
Physician housing return×Low ex ante C-section rate			1.614						
			(2.164)						
Physician housing return×Low physician density						2.164			
						(2.052)			
Physician housing return×Female physician									2.619
									(2.265)
Patient covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	34.68	45.74	40.20	40.73	39.53	40.19	39.28	41.34	40.19
Observations	94,230	93,643	187,873	102,543	85,330	187,873	104,784	83,089	187,873

Panel B: Low-risk patients	*C-section rate ex ante*			*Physician density*			*Physician gender*		
	(1) Low	(2) High	(3) All	(4) Low	(5) High	(6) All	(7) Female	(8) Male	(9) All
Physician housing return	4.806	0.688	0.688	4.564	0.693	0.693	5.857	1.353	1.353
	(1.685)	(2.187)	(2.182)	(1.505)	(2.078)	(2.045)	(1.558)	(2.281)	(2.260)
Physician housing return×Low ex ante C-section rate			4.117						
			(2.757)						
Physician housing return×Low physician density						3.870			
						(2.549)			
Physician housing return×Female physician									4.504
									(2.750)
Patient covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	17.99	27.71	22.74	23.69	21.53	22.71	22.09	23.55	22.73
Observations	68,264	65,287	133,551	72,666	60,885	133,551	74,884	58,667	133,551

Notes: This table reports results from subsample regressions of the C-section indicator on physician housing returns, estimated using a linear probability model. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The C-section indicator is scaled by 100. Columns (1)–(2) divide the sample by physicians' ex ante excessive C-section rates; Columns (4)–(5) by local physician density; Columns (7)–(8) by physician gender. Columns (3), (6), and (9) includes interaction terms between physician housing returns and sample dividers. All regressions include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A10. Effects on Other Treatment Margins (by Delivery Mode)

Panel A: All patients

	Cesarean births			Vaginal births		
	(1) Induction	(2) Vacuum/Forceps	(3) Hosp. charges	(4) Induction	(5) Vacuum/Forceps	(6) Hosp. charges
Physician housing return	-0.625	0.138	0.001	-0.985	1.417	0.011
	(1.049)	(0.750)	(0.009)	(1.159)	(0.654)	(0.008)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	8.14	3.96	9.69	22.31	6.05	9.12
Observations	75,485	75,485	75,485	112,388	112,388	112,388

Panel B: Low-risk patients

	Cesarean births			Vaginal births		
	(1) Induction	(2) Vacuum/Forceps	(3) Hosp. charges	(4) Induction	(5) Vacuum/Forceps	(6) Hosp. charges
Physician housing return	-0.620	-0.704	-0.013	-1.763	1.723	0.010
	(2.881)	(1.062)	(0.013)	(1.247)	(0.684)	(0.009)
Patient covariates	✓	✓	✓	✓	✓	✓
Physician FE	✓	✓	✓	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	18.34	3.72	9.75	23.19	6.16	9.11
Observations	30,330	30,330	30,330	103,221	103,221	103,221

Note: This table reports results from regressions of other treatment margins on physician housing returns by delivery mode. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1)–(3) include cesarean births and Columns (4)–(6) include vaginal births. Columns (1) and (4) use an indicator (scaled by 100) for labor induction as the outcome; Columns (2) and (5) use an indicator (scaled by 100) for vacuum/forceps; Columns (3) and (6) use logged hospital charges. All columns include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

Table A11. Effects on Length of Stay (Poisson Model)

Panel A: All patients

	Length of stay		
	(1) Total	(2) Pre-birth	(3) Post-birth
Physician housing return	0.009	-0.068	0.016
	(0.007)	(0.047)	(0.006)
Patient covariates	✓	✓	✓
Physician FE	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓
Mean (dep. var.)	2.54	0.30	2.25
Observations	187,873	187,873	187,873

Panel B: Low-risk patients

	Length of stay		
	(1) Total	(2) Pre-birth	(3) Post-birth
Physician housing return	0.006	-0.053	0.011
	(0.008)	(0.048)	(0.007)
Patient covariates	✓	✓	✓
Physician FE	✓	✓	✓
Hospital×year-quarter FE	✓	✓	✓
Patient zip code×year-quarter FE	✓	✓	✓
Mean (dep. var.)	2.46	0.35	2.12
Observations	133,551	133,551	133,551

Note: This table reports results from patient-level regressions of patient length of stay (unit: days) on physician housing returns, estimated using Poisson models. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1)–(3) use the number of days for total hospital stay, pre-birth stay, and post-birth stay, respectively, as dependent variables. All columns include patient characteristics and fixed effects as in the baseline specification. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

B Sample Construction

Hospital Inpatient Records and Physician Characteristics. I begin with Florida's hospital inpatient discharge records and extract all inpatient records associated with labor and delivery.[1] Specifically, I keep discharges with an DRG code in the following set: 370, 371, 765, 766, 372, 373, 374, 375, 767, 768, 774, and 775. Among these, DRG codes 370, 371, 765, and 766 indicate cesarean deliveries, while codes 372, 373, 374, 375, 767, 768, 774, and 775 indicate vaginal deliveries.

For each discharge, I observe unique identifiers for both attending and operating physicians. Two types of physician identifiers are available: (1) license IDs, which are available for all years, and (2) NPIs, which are available only from 2010 onward. License IDs allow me to link physicians to Florida's healthcare practitioner profiles.[2] NPIs enable linkage to the National Provider Identifier (NPI) registry of the National Plan and Provider Enumeration System (NPPES).[3] About 96–99% of physicians can be matched to either the licensee profiles or the NPPES registry.

I apply the following filters based on physician identifiers. First, I exclude physicians with license IDs of "nan," "999999999," or those shorter than two digits. Second, I keep physicians with license IDs that begin with one of the following prefixes: "MD," "ME," "OS," "TRN," "UO," or "ACN." These prefixes correspond to physicians, as opposed to nurses or midwives. Specifically, "TRN" and "UO" indicate resident physicians in training. Third, I focus on physicians with both non-missing license IDs and NPIs. This restriction effectively limits the sample to physicians who continue to appear in the data after 2010, ensuring that they can be linked to the NPPES registry.

I follow La Forgia (2022)'s program for coding maternal risk factors using ICD codes that indicate risks present at the time of admission.[4] For maternal morbidity, I follow the methodologies of Johnson and Rehavi (2016), Freedman and Hammarlund (2019), La Forgia (2022), Callaghan et al. (2012), Kilpatrick et al. (2016), and CDC, using ICD codes to identify complications *not* present at the time of admission.[5]. Appendix Table B1 summarizes the codes used for maternal morbidity.

[1] https://quality.healthfinder.fl.gov/Researchers/Order-Data/

[2] https://mqa-internet.doh.state.fl.us/mqasearchservices/healthcareproviders/practitionerprofilesearch

[3] https://npiregistry.cms.hhs.gov/search (accessed on 2022/09/21).

[4] https://pubsonline.informs.org/doi/suppl/10.1287/mnsc.2022.4571

[5] https://www.cdc.gov/reproductivehealth/maternalinfanthealth/smm/severe-morbidity-ICD.htm

Table B1. ICD Codes for Maternal Morbidity

Maternal morbidity	Diagnosis code (DX)	Procedure code (PR)
Hemorrhage	666	
Infection	670 672 659.2 659.3	
Laceration	664.2 664.3 665.3 665.4 674.2	
Severe	410 441 584.5 584.6 584.7 584.8 584.9 669.3 518.5 518.81 518.82 518.84 799.1 673.1 427.41 427.42 427.5 286.6 286.9 641.3 666.3 642.6 997.1 046.3 348.39 362.34 430 431 432 433 434 435 436 437 671.5 674.0 997.02 428.0 428.1 428.20 428.21 428.23 428.30 428.31 428.33 428.40 428.41 428.43 428.9 518.4 668.0 668.1 668.2 995.4 995.86 038 449 785.52 995.91 995.92 998.02 670.2 669.1 785.50 785.51 785.59 995.0 998.0 998.00 998.01 998.09 282.42 282.62 282.64 282.69 289.52 415.0 415.1 673.0 673.2 673.3 673.8	31.1 96.7 99.0 99.6

Physician House Holdings. I begin with all ownership transfer records and mortgage records from CoreLogic. I then keep records that satisfy the following two conditions: (1) the property is located in Florida, and (2) the property type falls into one of the following categories: single-family residence, condominium, commercial property, duplex, or apartment. Restricting the sample to properties physically located in Florida is a practical solution, as searching for house ownership by name at the national scale is challenging. Alternatively, one could focus on properties where the "Buyer Mailing State" is listed as Florida, but this field in CoreLogic is prone to missing values.

For each physician extracted from the discharge records, I search the ownership transfer records to identify any associated transactions. I first standardize the documented names from the physician files. For each physician, I construct a name combination in the format: *Last Name + First Name + Middle Name Initial*. Most physicians have a complete name combination, except for a few cases where names are missing in either the licensee profiles or CMS data. For each transaction record, I standardize the buyer and seller names. If multiple names are listed in the buyer or seller fields, I collect all names into a list. I then search for house transactions where either the buyer or the seller matches a physician. This search is conducted by *role* in the transaction, categorized as follows: (1) "BUYER 1," (2) "BUYER 2," (3) "BUYER 3," (4) "BUYER 4," (5) "SELLER 1," and (6) "SELLER 2."

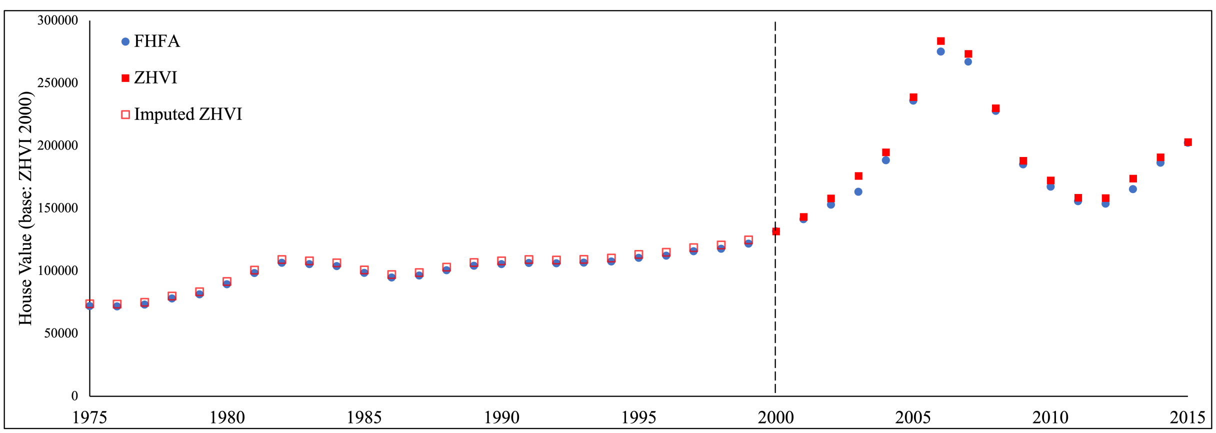
I construct physicians' housing portfolios step by step. First, I exclude house transactions that lack key information, including property ID, property location zip code, transaction date, and sales amount. I then collapse the transaction-level data to the physician×house×date level. To achieve this, I first collapse the data to the physician×house×date×role level. For example, if a physician appears in multiple "BUYER X" fields, I keep only the "BUYER" role. For each house, I keep the earliest purchase record and the latest sale record.

Next, I calculate the number of transaction records associated with each physician×house pair. I drop physicians with more than two transaction records for the same house, as these are likely duplicate entries for the same transaction. As a result, there are four possible transaction types for each physician×house pair. (1) Sell-first-then-buy: these pairs are dropped. (2) Buy-first-then-sell: these pairs are retained. (3) Buy-only: these pairs are retained. (4) Sell-only: for these records, I assign a pseudo purchase year based on the median purchase year within the same 5-digit zip code. For zip codes without sufficient data, I assign the median purchase year at the state level. These pairs are then reclassified as "buy-first-then-sell" and retained.

After this step, I drop physicians who have transacted more than 10 different houses over the years, as these are likely poor matches caused by common names. Lastly, I merge in mortgage information. This final step does not result in any loss of observations. Houses without matched mortgage records are assumed to have been purchased in cash.

House Prices. The Zillow House Value Index (ZHVI) is only available starting from the year 2000.[6] However, some physicians purchased their houses before 2000. To avoid excluding these physicians from the analysis, I impute the missing ZHVI values using the Federal Housing Finance Agency (FHFA) House Price Index.[7] Although published only annually, the FHFA index dates back to the 1970s and is also available at the zip code level (Bogin et al., 2019). For each zip code that has data in both ZHVI and FHFA after 2000, I calculate an average conversion ratio between the two indices: $\gamma = \frac{1}{T}\sum_{2000 \le t \le T}^{T} \frac{HPI_t^{\text{ZHVI}}}{HPI_t^{\text{FHFA}}}$. This ratio captures the relative relationship between the two indices, even though they are expressed in different units and cannot be directly compared. The imputed ZHVI values for a given zip code before 2000 are then calculated as: $HPI_t^{\text{ZHVI}} = \gamma \cdot HPI_t^{\text{FHFA}}, \forall t < 2000$. Appendix Figure B1 below shows the average imputed ZHVI values foreach year before 2000 (i.e., the red hollow square).

Figure B1. Imputing ZHVI Using FHFA Price Index



[6] https://www.zillow.com/research/data/
[7] https://www.fhfa.gov/data/hpi