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

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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 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
Keywords: financial distress, physician behavior, patient health

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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.

Physicians' financial health is susceptible to various external shocks. As some of the highest earners in the country (Gottlieb et al., 2025), physicians 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. As a result, the health of their balance sheets can 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 implications for physicians' personal finance.

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). 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, physicians in poorer financial health may treat patients with different risk profiles. To explicitly

[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 investments in stocks or real estate.

address this concern, I link the real estate data to hospital discharge records in Florida, which enables me to condition 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 and Owings, 1996; Johnson and Rehavi, 2016). Second, it is well documented that C-sections generally pay more than vaginal deliveries (Corry et al., 2013), and are often viewed as a strategy of defensive medicine that helps mitigate malpractice risk (Currie and MacLeod, 2008).[2] I therefore hypothesize that physicians in worse financial condition are more likely to 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 since the time of purchase. 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) or 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

[2] Section II discusses the tradeoff between vaginal delivery and C-section in detail.

26% (Gruber and Owings, 1996).

To confirm that the increase in C-section rate is not driven by physicians cherry-picking certain patients or by patients self-selecting into certain physicians, I show through a balance test that physician housing returns are conditionally independent of observed patient demographics and risk factors. I also 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.

The average effect masks substantial heterogeneity by physician characteristics. Those who performed fewer excessive C-sections ex ante, who practice in less competitive markets, and female physicians, are more responsive to lower housing returns. The effect is also unequal for different patients. 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, as it is less costly for physicians to recommend them inappropriate treatments.

One might wonder if the higher C-section rate results from physicians using less assisted methods during attempted vaginal deliveries. I consider two examples of such methods—induction and ancillary procedures. There is no evidence for reduced use of induction in the first stage of labor; if anything, the use of ancillary procedures during the second stage slightly increases. 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 health 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 these 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 to observe physician responses even when house values are rising. 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 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.[3] To the best of my knowledge, this paper is the first to measure housing wealth shocks at the individual physician level.[4] Furthermore, my regression design controls for hospital$\times$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 worker performance 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, pro-

[3]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 which causes more cases of COVID-19.

[4]A related paper is Erel et al. (2024), which studies how real estate shocks affect physician-level opioid prescriptions.

ducing potential externalities on public health. Importantly, the inpatient-level healthcare data also allows 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.

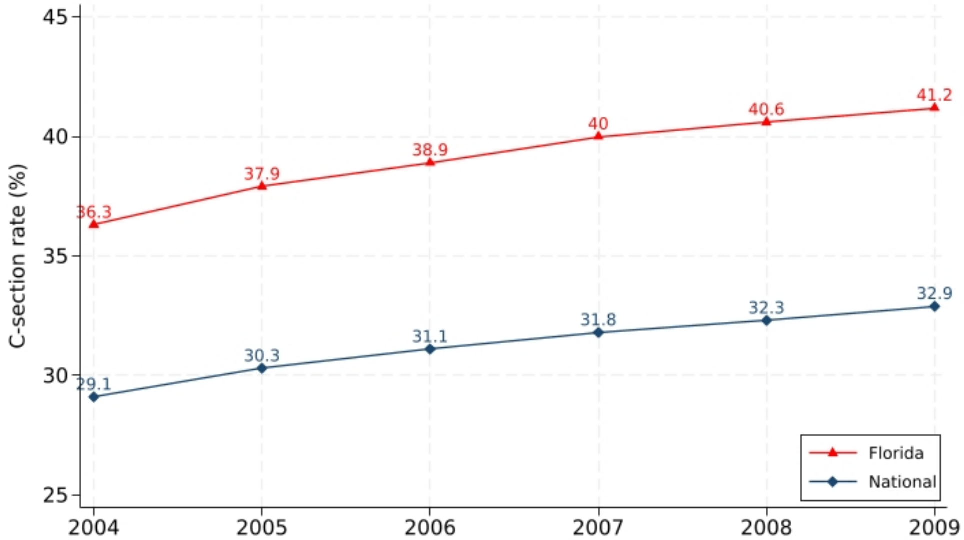
Finally, this paper advances the healthcare literature on physician-induced demand, particularly in the context of childbirth. Prior work has uncovered financial incentives (Gruber and Owings, 1996; Gruber et al., 1999), malpractice pressures (Wagner, 2000; Dranove and Watanabe, 2010), information asymmetry (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, and Section III introduces the data and empirical design. I report the main results in Section IV and explore underlying mechanisms in Section V. Section VI concludes the paper.

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). Both datasets include all types of C-sections.

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. C-sections can also be requested by patients. Among all Florida patients who receive scheduled C-sections, about a quarter are perceived as low-risk. 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 an emergency C-section (i.e., an unscheduled C-section). The diagnosis of these conditions 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 complications such as infection, hemorrhage, and blood clots during 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 also negatively affect infants, 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 and Owings, 1996; 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 and about 10%–20% higher in more recent years for both Medicaid and commercial insurers (Corry et al., 2013).[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 deciding which medical treatment a patient should receive. C-sections appear to be more rewarding for physicians than vaginal deliveries. Given the financial incentives, I therefore assume that physicians in weaker financial positions are more motivated to adopt C-sections throughout the empirical analysis. I further discuss the potential mechanisms behind this assumption and findings in Section V.

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

[6] Using data from MarketScan during 2004–2010, Corry et al. (2013) report that commercial insurers paid an average of $3,350 and $2,887 for cesarean and vaginal deliveries as professional service fees, respectively (Medicaid paid $1,654 and $1,445, respectively). Physicians may also receive higher reimbursements from cesarean-related services (e.g., anesthesiology, laboratory, radiology, and pharmacy fees) and, in some cases, additional dividends from their ownership in the facilities. There are also financial incentives at the hospital level. 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. This data includes 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, insurer type, as well as diagnoses and procedures via ICD-9 codes. The data also allows 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. For example, between the first quarter of 2007 and the fourth quarter of 2009, the dataset identifies 560,855 childbirths, approximately 40% of which were delivered via C-section.

An key advantage of the Florida inpatient data is that it contains 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, gender, and practice location for all medical doctors on file. I then supplement this 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, 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 exclude 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 excluded. I also drop patients whose physicians never performed a C-section during the sample period, 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 attend, regardless of patient characteristics, individual risk factors, or aggregate risk.

Panel B of Table 1 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 $544,212 (in 2006 constant dollars) and had owned them for approximately five years by the end of 2006.

[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.

Table 1. Summary Statistics

Sample	*Unmatched physicians* Mean	SD	*Matched physicians* 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]
Charlson Index	0.031	[0.207]	0.030	[0.202]
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)	18.837	[9.811]	17.868	[8.951]
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 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 aggregates of patient data, 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.

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 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 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 cumulative housing return, as shown in Equation (1) below.

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

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.[9] 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 two key 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 prior research shows that physicians often target their income to specific reference levels (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).

Compared to market-level indicators of house price movements, $R_{j,t}$ is less likely to be confounded by unobserved factors that simultaneously influence patient demand, as it incorporates 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 zip codes. Appendix Figure A1 maps the number of physicians residing in each Florida zip code. These areas exhibit heterogeneous price trends, even within the same recession period (Bogin et al., 2019). Appendix Figure A2

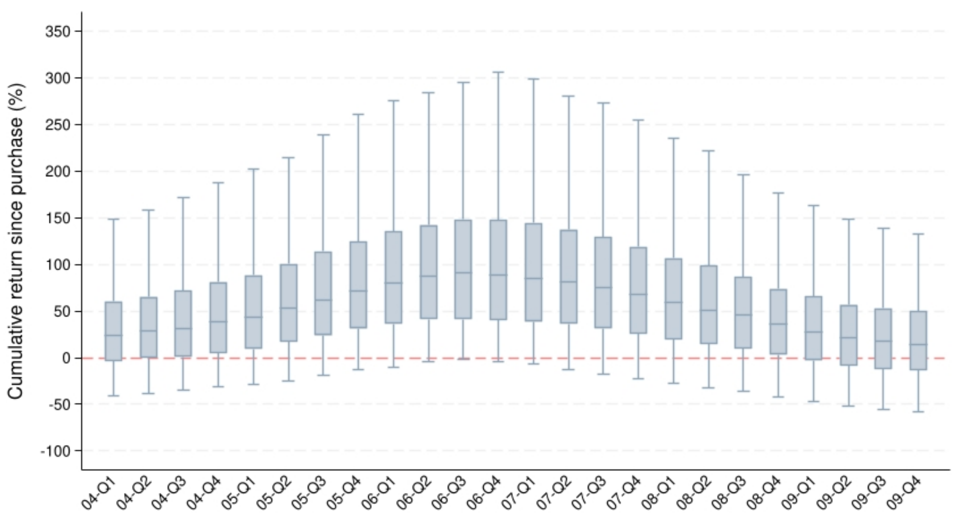
[8] ZHVI measures the typical value of homes in the 35th to 65th percentile range of a local market. It is smoothed, seasonally adjusted, and available from 2000 onward. For earlier years, I impute values using the Federal Housing Finance Agency (FHFA) house price index. Appendix B provides details of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

[9] Appendix Table A7 shows that results are robust to using time-varying portfolios.

illustrates the variation in ZHVI percentage changes across zip codes during 2007–2009. The second source of heterogeneity comes from the timing of house purchases (t_0). Appendix Figure A3 shows the distribution of purchase years, which has a long left tail with over half of the physicians becoming homeowners after 2000. Note that even physicians living in the same zip code can experience different housing returns, depending on their purchase timing. Appendix Figure A4 highlights this variation by showing the distribution of simulated cumulative returns for physicians living in different zip codes, assuming home purchases in 2000 versus 2006.

Combining these two dimensions of physician-level heterogeneity, $R_{j,t}$ offers useful variation for identification, which I elaborate on 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 analyzed in this study.

Figure 2. Distribution of Physician Housing Returns



Notes: This boxplot shows the distribution of housing returns among physicians 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 calendar year-quarter. On the left-hand side of Equation (2), $y_{i,j,h,t}$ represents the main outcome variable of interest in the case of childbirth, $1\{C-section\}_{i,j,h,t}$, 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 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.

This baseline specification controls for a comprehensive set of patient characteristics, $\mathbf{X}_i$, including demographics (e.g., race and ethnicity), insurance type (e.g., Medicaid or commercial), weekend delivery status, and 24 clinical risk factors observed before labor onset (e.g., prior C-section, advanced maternal age, 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.[10]

Equation (2) also includes physician fixed effects, μ_j, to account for time-invariant physician characteristics. Physicians may differ in their skills—-some may be better at performing C-sections or diagnosing patients in need of C-sections (Epstein and Nicholson, 2009; Currie and MacLeod, 2017). If such physicians systematically sort into areas that experienced steeper house price declines, failing to account for this could bias the estimated effect of financial shocks. Physician fixed effects therefore help mitigate this concern by controlling for persistent differences in practice style and physician preferences.

Finally, I include two additional 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×year-quarter fixed effects, $\delta_{h,t}$, in Equation (2), which helps to isolate supply-side

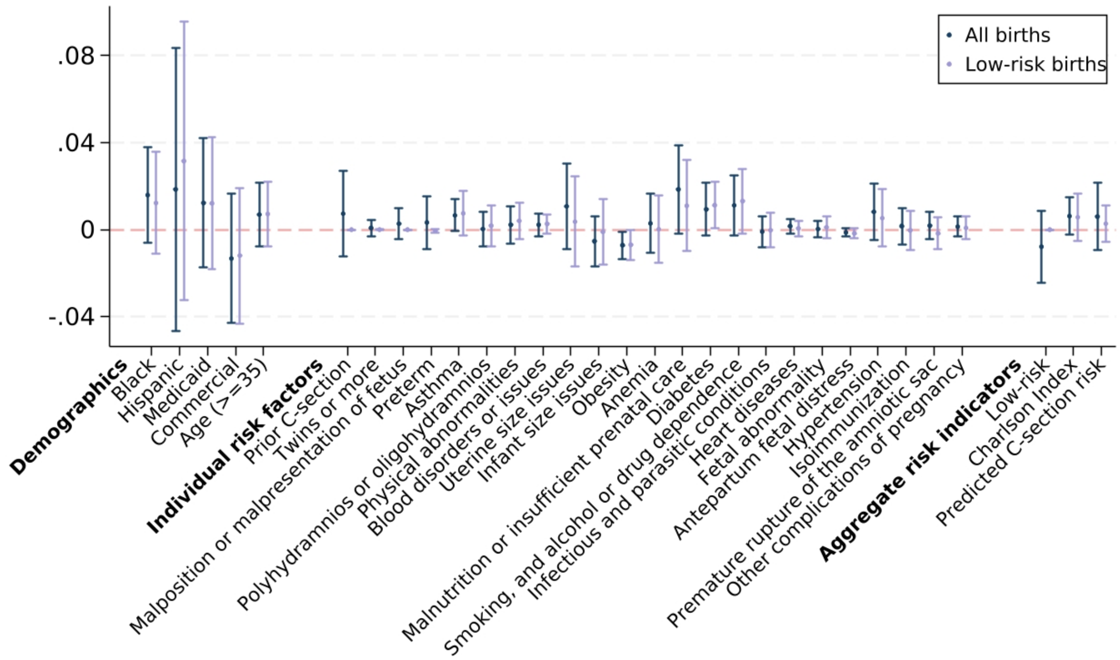
[10] Similar risk factors are also used by previous studies (Henry et al., 1995; Gregory et al., 2002; Johnson and Rehavi, 2016; Currie and MacLeod, 2017; La Forgia, 2022). Appendix Table A1 shows that most of them are strong predictors of C-section risk.

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 who are 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 alleviate this concern, I leverage the availability of patients' residential zip codes in the inpatient data and include patient zip code×year-quarter fixed effects, $\eta_{c,t}$, in Equation (2). This helps to absorb latent demand-side factors to a good extent, even if such unobservables are time-varying.

The identification of Equation (2) relies on the conditional independence assumption. That is, conditional on patient covariates, physician, hospital×year-quarter, and patient zip code×year-quarter fixed effects, 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 characteristics are balanced across physician housing returns. Specifically, I regress each of the patient characteristics in $\mathbf{X}_i$ on physician housing return, including the calender year-quarter and physician fixed effects. Figure 3 presents the estimated coefficients for physician housing return from these individual regressions—they are generally close to zero and statistically insignificant with few exceptions (e.g., obesity). Regressions using aggregate risk measures—such as clinical low-risk status, the Charlson Index, and predicted C-section risk—yield similar results. Lastly, I run a reverse regression with physician housing return as dependent variable and all the patient risk factors as independent variables. A joint significance test on these risk factors produces an F-statistics of 1.41 (p-value=0.100). Overall, these findings suggest that patient characteristics are conditionally balanced across physicians exposed to different levels of wealth shocks, lending credibility to the conditional independence assumption.

Figure 3. **Balance Test**



Notes: This figure presents the results of the balance test, as described in Section III.C. Each point represents a coefficient estimate from a separate regression of the row variable on physician housing returns (reversed in sign), with 95% confidence intervals shown. The row variables include patient demographics, individual risk factors, and aggregate risk indicators. Housing returns are calculated as cumulative returns since the time of purchase. All regressions include calendar year-quarter and physician fixed effects. 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.

The identification also requires that, conditional on patient covariates and the fixed effects, other unobserved physician characteristics that may affect patient treatments are mean independent of physician housing return (i.e., the exclusion restriction). While this assumption is difficult to test directly, it appears plausible for several reasons. First, by construction, physicians' housing portfolios are fixed prior to the onset of the Great Recession and are therefore unlikely to be correlated with factors that influence their treatment behavior ex post. Although one might worry that physicians could have anticipated the housing crisis and made strategic investment or divestment, prior studies such as Cheng et al. (2014) have shown that even financial professionals have 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). Second, physician fixed effects have accounted for differences in housing returns that is determined by the choice of location and timing of home purchases. The remaining within-physician variation is primarily driven by house price movements at more aggregate levels, and can be thought of as good as that from randomly exposing physicians to different extents of financial shocks in a quasi-experiment. Lastly, the inclusion of physician fixed effects alongside year-quarter fixed effects (through $\delta_{h,t}$ and $\eta_{c,t}$) implicitly absorbs time-varying physician characteristics that evolve linearly over time, such as age or years of work experience, even if they are not explicitly included in the model. Admittedly, the aforementioned controls cannot fully eliminate all sources of endogeneity. However, any remaining threats to identification would need to be correlated with physician housing returns in a time-varying manner.

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. That said, Appendix Table A1 confirms that results are robust to alternative non-linear models such as Logit. Unless otherwise noted, I cluster standard errors at the physician level throughout the main analysis. Appendix Table A2 reports similar results when standard errors are clustered at more conservative levels, including hospital, patient zip code, and physician zip code.

IV Results

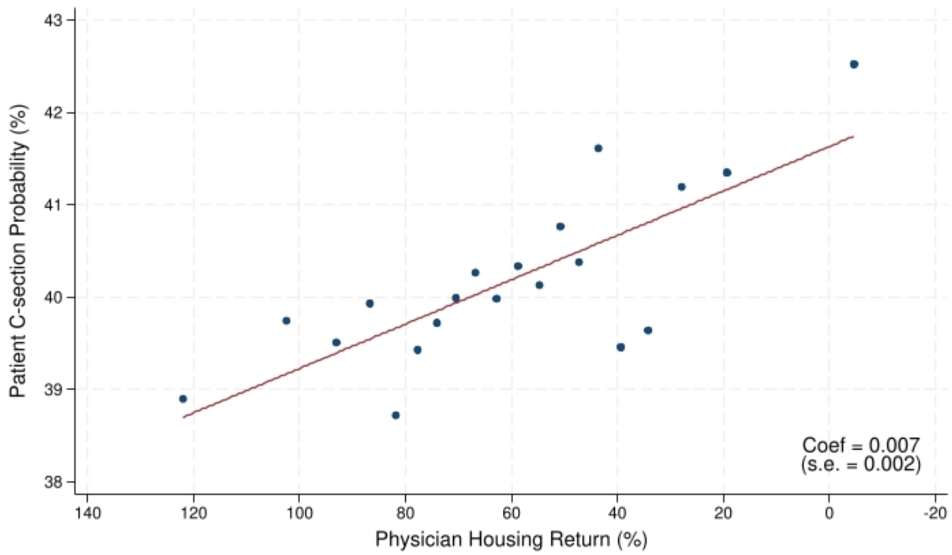
This Section provides the empirical results. I start by estimating the effect of physicians' financial health on the main treatment margin—vaginal delivery versus C-section—in subsection IV.A. I then explore these heterogeneous effects by physician and patient characteristics in subsections IV.B and IV.C. I also examine the effect on other treatment margins in subsection IV.D, and the impacts on patient health in subsection IV.E. Lastly, I report a battery of robustness checks in subsection IV.F.

IV.A Effects on Physician Treatment Choices

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 ten equally 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.

To further investigate how financial shocks influence treatment decisions, I estimate linear regressions 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)

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 10 equal-sized bins based on their physicians' cumulative housing returns since purchase (expressed in percentage points), shown on the horizontal axis. For each bin, the average probability of C-section 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).

adds hospital×year-quarter fixed effects to account for hospital-level incentives and responses. The estimated effect becomes larger in magnitude and more statistically significant.

A major concern of endogeneity is that 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. However, I have explicitly controlled for a rich set of patient characteristics in the regressions and shown that these characteristics are balanced across physicians (Figure 3). In other words, the effect is not likely driven by selection on observed patient characteristics. 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) 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 ($\approx$ 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.[11] 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, C-sections may also be performed at the request of patients. To rule out the possibility that the results thus far are driven by patient preferences, I separately examine the effects on unscheduled and scheduled C-section rates, as maternally requested C-sections are typically scheduled in advance. Unscheduled C-sections are defined as those associated with ICD diagnosis codes indicating a trial of labor (Henry et al., 1995; Gregory et al., 2002). In Florida, approximately 77% of all C-sections are scheduled, though not all are maternally requested. I hypothesize that the effect of housing shocks will be weaker for scheduled C-sections compared to unscheduled cases. Columns (4) and (5) of Table 2 use unscheduled and scheduled C-section probabilities as the outcome variables, respectively. Physician housing return significantly predicts the rate of unscheduled C-sections, but not scheduled ones, suggesting that the observed increase in C-section rates is concentrated in cases where patient preferences are likely minimal.

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.[12] Low-risk patients are generally considered strong 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 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

[11] 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) estimate 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. Combining these estimates, a 1.6 percentage point is therefore equivalent to the effect of lowering the pay differential by about $1.6/(\frac{0.7+0.6}{2}) \times \$100 \approx \$250$.

[12] 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.

demand-side factors are driving the observed increase in C-section rates.

Table 2. Effects on Treatment Choices

Panel A: All patients					
	C-section			*Unscheduled C-section*	*Scheduled C-section*
	(1)	(2)	(3)	(4)	(5)
Physician housing return	1.615	2.383	2.379	1.953	0.426
	(0.834)	(0.965)	(1.023)	(0.628)	(0.884)
Year-quarter FE	X				
Patient covariates	X	X	X	X	X
Physician FE	X	X	X	X	X
Hospital-year-quarter FE		X	X	X	X
Patient zip code-year-quarter FE			X	X	X
Mean (dep. var.)	40.18	40.18	40.18	9.23	30.95
Observations	187,873	187,873	187,873	187,873	187,873

Panel B: Low-risk patients					
	C-section			*Unscheduled C-section*	*Scheduled C-section*
	(1)	(2)	(3)	(4)	(5)
Physician housing return	2.356	3.352	3.130	2.963	0.167
	(1.026)	(1.179)	(1.253)	(0.805)	(0.991)
Year-quarter FE	X				
Patient covariates	X	X	X	X	X
Physician FE	X	X	X	X	X
Hospital-year-quarter FE		X	X	X	X
Patient zip code-year-quarter FE			X	X	X
Mean (dep. var.)	22.71	22.71	22.71	11.26	11.45
Observations	133,551	133,551	133,551	133,551	133,551

Notes: This table reports baseline results from patient-level regressions of C-section indicators 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. C-section indicators are scaled by 100. Columns (1)–(3) indicate for any C-section, whereas Column (4) and (5) indicate for unscheduled and scheduled C-sections, respectively. All columns control for physician fixed effects and patient characteristics, including demographics, insurance type, weekend delivery, and clinical risk factors based on comorbidities observed prior to labor onset. Columns (2)–(5) additionally include hospital×year-quarter fixed effects. Columns (3)–(5) additionally include patient zip code×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 shown in parentheses.

IV.B Heterogeneous Effects by Physician Characteristics

The effect of financial health on physician treatment choices may vary across different providers. This subsection explores the heterogeneity in physicians' responses by focusing 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.[13] Columns (1) and (2) of Table 3 report results for two subsamples, split based on whether the physician's excessive C-section rate is above or below the median. Physicians with a lower excessive C-section rate are more likely to increase their C-section rates in response to lower housing returns. 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, it may constrain physicians' behavior, deterring inappropriate treatment decisions. 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. Columns (3) and (4) of Table 3 show that the effect is stronger in low-density markets, consistent with the idea that physicians in these areas are less disciplined by market competition and thus 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 financial conditions (Dunn and Shapiro, 2018; Brekke et al., 2019; Ikegami et al., 2021).

Lastly, I study if physician gender plays a role in affecting 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 be receive favorable evaluations and have lower mortality rates from physicians of the same gender. Results in Columns (5) and (6) of Table 3 show that patients are more likely to receive C-sections when their female physicians are financially shocked, suggesting that gender concordance 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.

[13] 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.

Table 3. Heterogeneous Effects by Physician Characteristics

Panel A: All patients	*C-section rate ex ante*		*Physician density*		*Physician gender*	
	(1) Low	(2) High	(3) Low	(4) High	(5) Female	(6) Male
Physician housing return	3.083	1.446	3.123	0.954	4.395	1.775
	(1.321)	(1.718)	(1.231)	(1.654)	(1.312)	(1.856)
Patient covariates	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
Mean (dep. var.)	34.68	45.74	40.73	39.53	39.28	41.34
Observations	94,230	93,630	102,543	84,916	104,784	83,089

Panel B: Low-risk patients	*C-section rate ex ante*		*Physician density*		*Physician gender*	
	(1) Low	(2) High	(3) Low	(4) High	(5) Female	(6) Male
Physician housing return	4.806	0.662	4.564	0.696	5.857	1.353
	(1.685)	(2.188)	(1.505)	(2.077)	(1.558)	(2.281)
Patient covariates	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
Mean (dep. var.)	17.99	27.71	23.69	21.54	22.09	23.55
Observations	68,264	65,282	72,666	60,603	74,884	58,667

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. C-section indicators are scaled by 100. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Columns (1)–(2) split the sample by physicians' ex ante excessive C-section rates; Columns (3)–(4) by local physician density; and Columns (5)–(6) by physician gender. 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.

IV.C Heterogeneous Effects by Patient Characteristics

The effect of financial health on physician treatment choices can also be unequal for different patients. Understanding the distributional effects is crucial for evaluating the welfare consequences of physician behavior and for designing more targeted policy interventions. In this subsection, I highlight the role of two patient-side factors that have been extensively 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. Columns (1) to (3) of Table 4 report the corresponding estimates. The effect is most statistically significant among non-Hispanic Black patients, with the magnitude more than twice as large as the average effect reported in Table 2. 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 estimated 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 from physicians, 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 physician 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 on those with minimal expected benefits even though facing financial incentives. In other words, patients with medium-level expected benefits are more likely to be shifted between the two delivery modes. To test this prediction, I first use all patients in the analytic sample and estimate a Logit regression model including a binary variable of C-section as outcome and all demographics and risk factors as predictors.[14] The predicted value from this model is interpreted as each patient's "appropriateness" for receiving a C-section. This approach follows prior work in assuming that, on average, physicians have performed the "correct" number of C-sections (Currie and MacLeod, 2017; Robinson et al., 2024).

Columns (4) to (6) of Table 4 present the estimates separately for three equally 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 by the low-risk definition. In fact, similar patterns are observed even when restricting the analysis to low-risk patients, as shown in Panel B of Table 4.

[14] Column (1) of Appendix Table A1 reports the result from this Logit regression.

Table 4. 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) Low	(5) Medium	(6) High
Physician housing return	6.894	1.193	1.318	2.163	5.516	1.574
	(2.124)	(1.498)	(1.324)	(1.563)	(2.121)	(1.443)
Patient covariates	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
Mean (dep. var.)	39.18	44.33	39.27	13.87	25.19	83.83
Observations	39,860	36,201	111,812	75,272	50,052	62,549

Panel B: Low-risk patients	*Patient race and ethnicity*			*Appropriateness of C-section*		
	(1) NH Black	(2) Hispanic	(3) Others	(4) Low	(5) Medium	(6) High
Physician housing return	8.441	3.247	1.312	2.014	6.053	5.619
	(2.674)	(2.051)	(1.647)	(1.571)	(2.271)	(5.165)
Patient covariates	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
Mean (dep. var.)	22.42	25.57	22.06	14.01	24.82	54.93
Observations	27,576	24,959	81,016	70,924	46,644	15,983

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. C-section indicators are scaled by 100. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Columns (1)–(3) split the sample by patient race and ethnicity; Columns (4)–(6) by patients' medical appropriateness of receiving a C-section. 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.

IV.D Effects on Other Treatment Margins

Previous sections have demonstrated that physicians adjust the major treatment choice in childbirth—C-section versus vaginal delivery—in response to negative financial shocks. An open question is whether physicians also respond along other treatment margins. This section examines three such dimensions: (1) alternative treatment options, (2) overall treatment intensity, and (3) the total number of childbirths attended.

To begin with, one might wonder whether the higher C-section rate is a result of physicians using less 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 (1) of Table 5 reports the result 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. Column (2) of Table 5 uses an indicator for vacuum/forceps as the outcome and finds that patients are slightly more likely to receive these procedures when physician housing returns decrease. In fact, the increased use of vacuum/forceps is concentrated in vaginal births (see Appendix Table A3).

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 (3) of Table 5 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 (see Appendix Table A3).

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 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 physician×year×quarter-level data set, controlling for physician and year×quarter fixed effects. Column (4) of Table 5 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 also be determined by demand-side factors beyond physicians' control, such as underlying fertility rates.

Table 5. Effects on Other Treatment Margins

Panel A: All patients	*Induction*	*Vacuum/Forceps*	*Hosp. charges*	*# Deliveries*
	(1)	(2)	(3)	(4)
Physician housing return	-0.527	0.966	0.008	-0.042
	(0.843)	(0.511)	(0.007)	(0.060)
Year-quarter FE				X
Physician FE	X	X	X	X
Patient covariates	X	X	X	
Hospital-year-quarter FE	X	X	X	
Patient zip code-year-quarter FE	X	X	X	
Mean (dep. var.)	16.63	5.22	9.35	41.51
Observations	187,873	187,873	187,873	5,678

Panel B: Low-risk patients	*Induction*	*Vacuum/Forceps*	*Hosp. charges*	*# Deliveries*
	(1)	(2)	(3)	(4)
Physician housing return	-1.154	0.998	0.003	-0.045
	(1.117)	(0.559)	(0.008)	(0.060)
Year-quarter FE				X
Physician FE	X	X	X	X
Patient covariates	X	X	X	
Hospital-year-quarter FE	X	X	X	
Patient zip code-year-quarter FE	X	X	X	
Mean (dep. var.)	22.15	5.62	9.26	41.78
Observations	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) and (2) use indicators (scaled by 100) for labor induction and vacuum/forceps use, respectively. Column (3) uses logged hospital charges. Columns (1)–(3) include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Column (4) 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.

IV.E Effects on Patient Health

Previous sections have shown that negative shocks to physicians' financial health influence their treatment choices, with patients from disadvantaged socio-economic backgrounds (e.g., Black patients) bearing disproportionate costs. To provide a more comprehensive picture on the effect on patient welfare, this section explores whether shifts in physician behavior translate into measurable differences in maternal health outcomes.

Theory offers ambiguous predictions regarding this issue. On the one hand, patient health outcomes may worsen if physicians, facing wealth losses from declining home values, are incentivized to adopt more profitable procedures, resulting in potential over-treatment that deviates from the clinical optimum. On the other hand, financially distressed physicians may practice more cautiously, aiming to avoid adverse outcomes by opting for more conservative interventions. In the meantime, as shown in Section IV.C, the patients most affected by these behavioral shifts are those who are closer 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 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. The first concerns the number of days a patient remains 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.[15] Column (1) of Table 6 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 similarly sized increase in inpatient length of stay.

To explore what drives the increase in length of stay, Columns (2) and (3) of Table 6 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 6 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.

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

[15] Poisson regressions using the length of stay as a count outcome yield similar results (see Appendix Table A4).

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.[16]

As shown in Columns (5) to (8) of Table 6, physician financial shocks do not significantly affect 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 6. Overall, I find no strong evidence that physicians' responses to negative financial shocks adversely 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 not captured by my data, such as long-term reproductive consequences (e.g., repeat C-sections) or mental health issues (e.g., postpartum depression). In addition, I am unable to assess the health impacts on infants due to data limitations.

[16]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, the estimated health effects should likely be interpreted as conservative lower bounds.

Table 6. 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	X	X	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X	X	X
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	X	X	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X	X	X
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 physician fixed effects, hospital$\times$year-quarter fixed effects, patient zip code$\times$year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. 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.

IV.F Robustness

Results of several additional robustness checks are summarized in Appendix Tables A5 to A7. I begin by adding an extended set of fixed effects to the baseline specification to rule out the possibility that the main results are driven by alternative selection channels. Next, I consider a range of alternative measures of physician financial shocks, all of which yield qualitatively similar findings. Finally, I show that the main results are not sensitive to certain specifications of sample construction.

Ruling Out Other Selection Channels. Previous sections have attempted to rule out alternative explanations from both supply-side and demand-side by conditioning the identification on a rich set of patient covariates, physician, hospital×time, and patient zip code×time fixed effects. Nonetheless, a more nuanced concern remains: patients may have unobserved preferences that lead them to selectively choose certain providers. If those providers are systematically more or less exposed to housing wealth shocks, the main estimates could be biased.

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 A5 shows that the estimate remains highly significant within this restricted sample. To further address this concern, I also include patient zip code×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 A5 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 her physician. These patients are arguably less likely to have a prior relationship with their physicians or to possess information about their physicians' financial health in advance. Column (3) of Appendix Table A5 shows that the result remains robust within this group. In a similar vein, I include patient zip code×physician fixed effects to control for time-invariant factors specific to each patient zip-physician pair. Column (4) of Appendix Table A5 reports consistent findings.

Finally, *physician-hospital* matching may also matter, as previous work such as Mourot (2024) has found that physician performance could be hospital-specific. In reality, this may be due to physicians' hospital privileges, employment affiliation, or other factors in their production functions. The policy implications would differ if the results simply captured physicians performing more C-sections at certain hospitals as opposed to an overall shift in their practice styles. To alleviate this concern, Column (5) of Appendix Table A5 restricts the sample to physicians who practice at only one hospital during the sample period (i.e., "single-homing" physicians). Column (6) additionally includes physician×hospital fixed effects in the regression. In both cases, the results remain consistent with the baseline estimates.

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 A6 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 housing returns. 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 A6 shows that a decline in this *quarter-over-quarter* return predicts an increase in C-section rates. I also 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 A6, is again consistent with the main hypothesis. Importantly, both the quarterly and annual return measures are less sensitive to the timing of a physician's home purchase, indicating that variation in house locations (i.e., zip codes) alone can provide meaningful variation in subsequent housing returns.

Lastly, I use the logged level of *house prices* as the main independent variable in the regression. House prices are computed as the (inflation-adjusted) purchase price multiplied by the cumulative housing return. Column (4) of Appendix Table A6 presents the result: C-section rates increase as physicians' house prices decline. The coefficient before 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 a 0.3 percentage point increase in the probability of C-section.

Alternative Sample 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 it ended in 2009 (i.e., early exits). The results, shown in Columns (1) to (3) of Appendix Table A7, show little change compared to the baseline estimates.

As noted earlier, I fix each physician's housing portfolio as of the end of 2006 when constructing 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 time-varying homeownership and track physician housing returns accordingly. The results, shown in Columns (4) to (6) of Appendix Table A7, remain remarkably similar to the baseline estimates.

V 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 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 Section V.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. Then, in Section V.B, I present empirical evidence to help differentiate the underlying mechanisms, guided by the predictions of the conceptual framework.

V.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' recommended treatment. 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).[17]

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 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:

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

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-

[17]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).

sections generally provide higher financial rewards than vaginal deliveries (i.e., $\omega_c > \omega_v$).[18] 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 (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 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 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), physician financial shocks, such as exogenous changes in W_j, can affect the probability of C-section through multiple mechanisms.

The first 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. 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.

[18] 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.

Another possible mechanism is financial distress, which unlike the wealth effect, only activates 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 under liquidity constraints may be particularly concerned about the broader consequences in addition to wealth losses, such as costs of loan default, mortgage foreclosure, or even personal bankruptcy (Bernstein, 2021; Dimmock et al., 2021; McCartney, 2021). As a result, they may resort to the more lucrative and legally safer treatment.

V.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 feer of real financial stakes causing physician distress.

Asymmetric Responses. A finding of asymmetric responses to positive and negative financial shocks would support the financial distress mechanism being more relevant than the wealth effect. 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 7 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 cumulative housing return across all physicians rose from below 25% at the beginning of 2004 to approximately 90% by the end of 2006. Columns (1) to (3) of Table 7 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.

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 around 2013. This trend aligns with the Federal Housing Finance Agency (FHFA) House Price Index showing 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 7 report results for the 2013–2015 period.[19] 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 7. Taken together, these findings sug-

[19]The Florida data used in this study ends 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.

gest that physicians do not reduce their use of C-sections in response to positive housing shocks.

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, as providers face fewer financial constraints during economic upturns. At face value, this result can 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.

Table 7. 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	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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 C-section indicators 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. C-section indicators are scaled by 100. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Columns (1)–(3) use 2004Q1–2006Q4 as the sample period; Columns (4)–(6) use 2013Q1–2015Q3 as the sample period. 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.

Physicians' Loan-To-Value Ratios. Physicians in greater debt are more economically vulnerable and thus more likely to experience financial distress. For these physicians, C-sections may become especially attractive because they offer higher payments and thus greater liquidity. Additionally, C-sections may 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. Based on these reasons, I 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%. Columns (1) to (3) of Table 8 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.

Table 8. **Effects by Physician Loan-To-Value Ratios**

Panel A: All patients						
	Physicians LTV: $\geq$ 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	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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: $\geq$ 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	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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. C-section indicators are 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 physician fixed effects, hospital$\times$year-quarter fixed effects, patient zip code$\times$year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. 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.[20]

[20]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).

VI 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. This effect is most pronounced among physicians who previously performed fewer excessive C-sections, those practicing in less competitive markets, and female physicians. Patients who are more likely to be affected include non-Hispanic Black patients and those with moderate expected benefits from C-sections. Physicians' responses are concentrated along the delivery mode margin, rather than through changes in overall patient volume. Importantly, I find no decisive evidence that these shifts in physician behavior substantially affect patient health outcomes.

I interpret these findings through a conceptual framework that incorporates financial incentives and patient welfare as key drivers of physician decision-making. The framework incorporates two channels through which negative financial shocks may encourage more C-sections: the wealth effect and financial distress. 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. Results in this paper suggest that these initiatives may prevent physicians from sliding into financial distress and, in doing so, support healthcare delivery. Notably, the federal student loan programs are expected to be scaled back by July 2026 under the One Big Beautiful Bill Act, raising concerns about provider vulnerability during future downturns.

The limited evidence for a wealth effect also aligns with prior research which documents that substitution effects often dominate income effects in physician behavior, emphasizing the effectiveness of physician payment regulation. 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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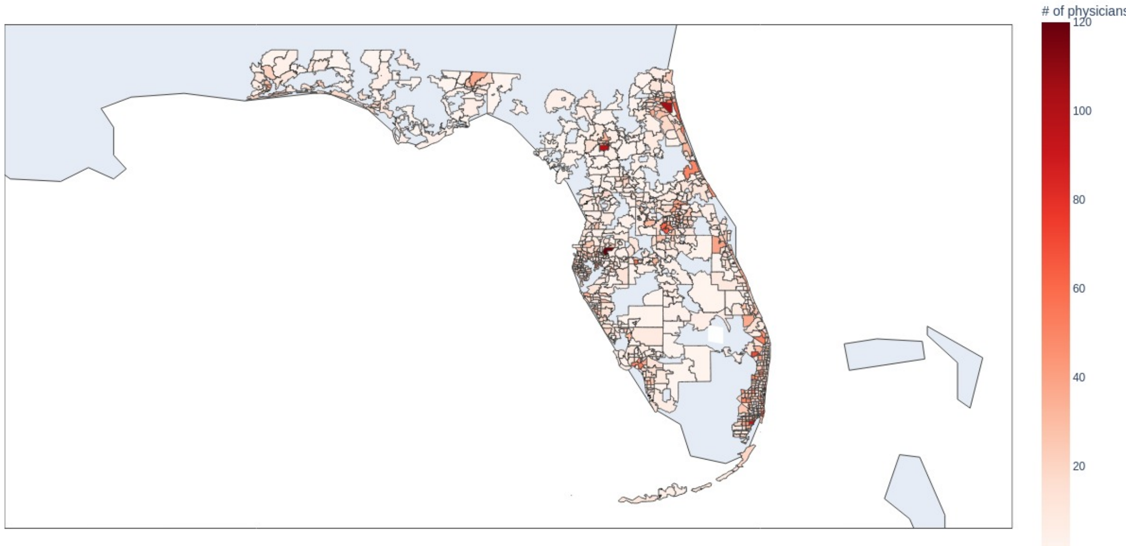
Online Appendix

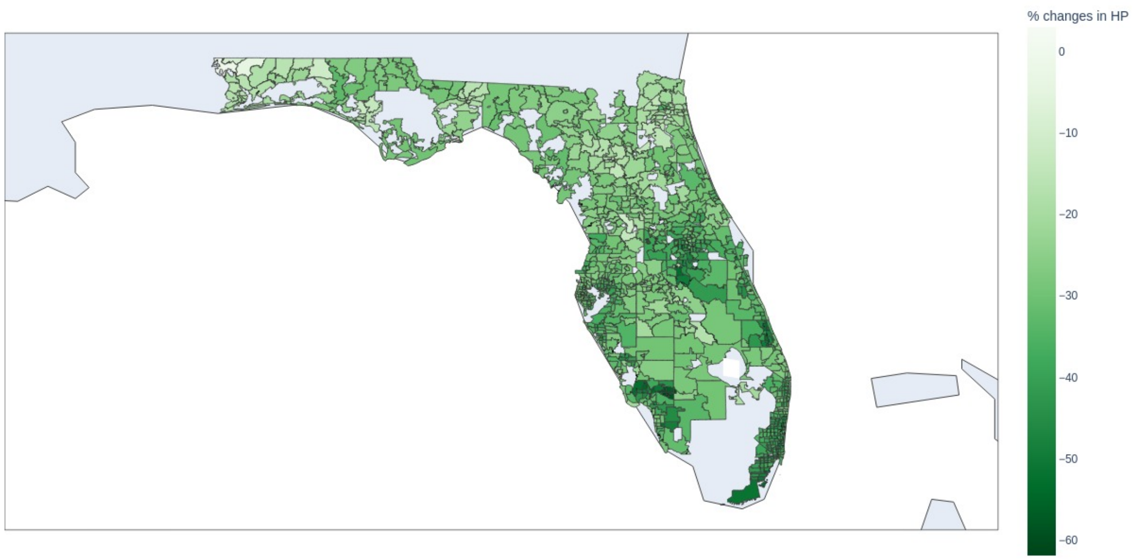
A Additional Figures and Tables

Figure A1. Number of Physicians in Each Zip Code



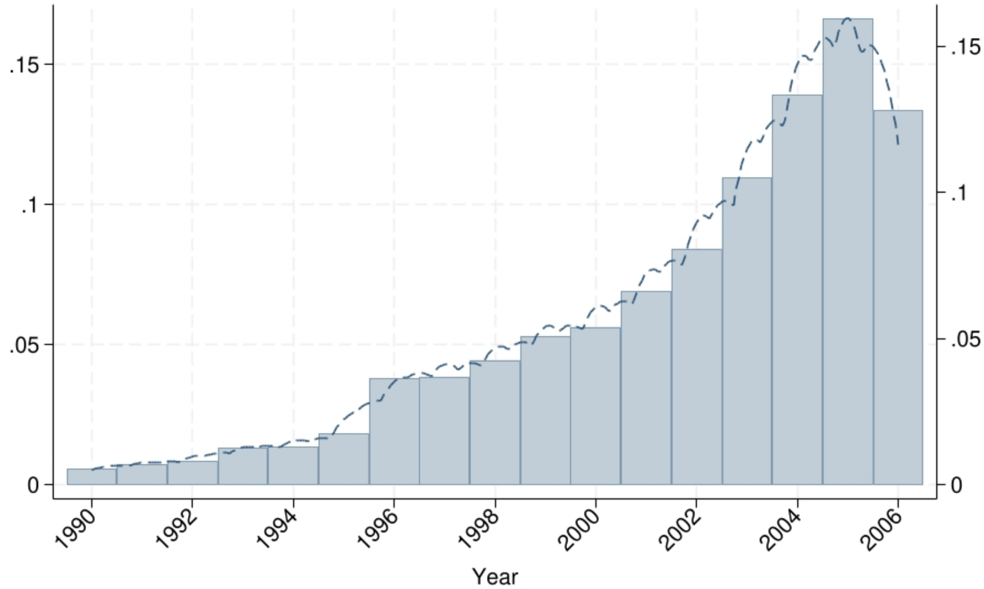
Notes: This figure shows the number of physicians residing in each Florida zip code. Physicians' residences are identified following the procedures described in Appendix B. Only houses held at the end of 2006 are included (i.e., excluding houses sold before 2006 or purchased after 2007). Zip codes with missing data are omitted.

Figure A2. $\%\triangle$ **Zillow Home Value Index in Each Zip Code**



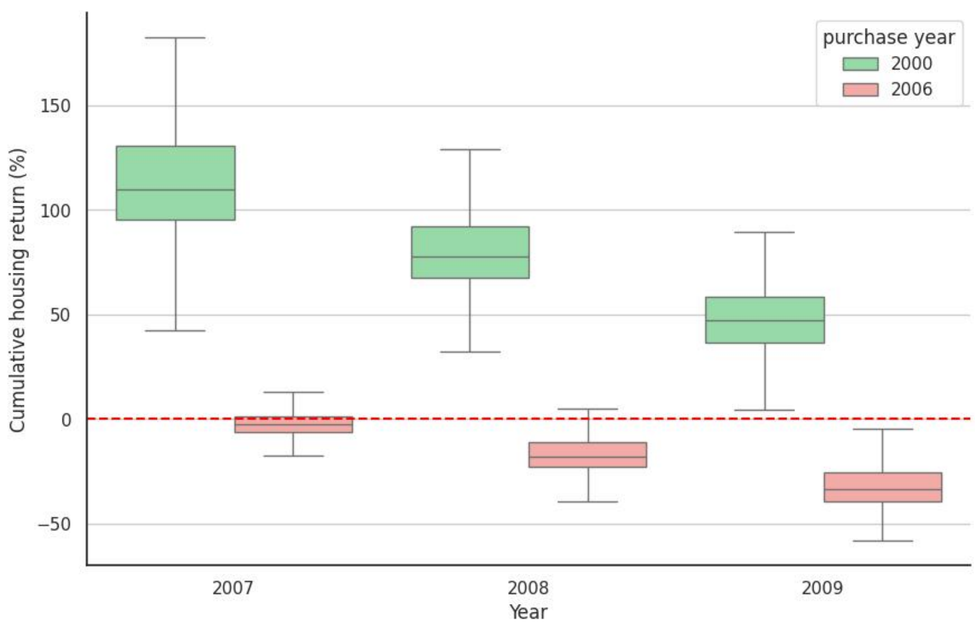
Notes: This figure displays the percentage change in the Zillow Home Value Index (ZHVI) for each Florida zip code from 2007 to 2009. Zip codes with missing ZHVI data are excluded.

Figure A3. **Fractions of Physicians in Different Purchasing Years**



Notes: This histogram shows the fraction of physicians who purchased houses each year. 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 estimate.

Figure A4. **Cumulative Returns by Different Purchasing Years**



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

Table A1. Nonlinear Probability Model

	All patients			*Low-risk patients*		
	(1)	(2)	(3)	(4)	(5)	(6)
Logit models						
Physician housing return			0.157			0.169
			(0.064)			(0.067)
Black	-0.026	-0.074	-0.074	0.034	-0.025	-0.025
	(0.039)	(0.024)	(0.024)	(0.038)	(0.025)	(0.025)
Hispanic	0.237	-0.025	-0.025	0.235	-0.029	-0.030
	(0.048)	(0.023)	(0.023)	(0.049)	(0.024)	(0.024)
Weekend delivery	-0.252	-0.214	-0.214	-0.212	-0.170	-0.170
	(0.028)	(0.021)	(0.021)	(0.027)	(0.022)	(0.022)
Medicaid	0.163	0.140	0.140	0.125	0.108	0.108
	(0.038)	(0.028)	(0.028)	(0.040)	(0.030)	(0.030)
Commercial	0.317	0.279	0.279	0.260	0.246	0.246
	(0.044)	(0.030)	(0.030)	(0.043)	(0.032)	(0.032)
Prior C-section	4.638	4.813	4.813	0.000	0.000	0.000
	(0.074)	(0.073)	(0.073)	(.)	(.)	(.)
35 years of age or older	0.216	0.164	0.164	0.246	0.198	0.198
	(0.020)	(0.019)	(0.019)	(0.022)	(0.021)	(0.021)
Hypertension	0.833	0.950	0.950	0.769	0.869	0.869
	(0.030)	(0.026)	(0.026)	(0.031)	(0.028)	(0.028)
Infectious and parasitic conditions	0.741	0.877	0.877	0.819	0.935	0.935
	(0.057)	(0.054)	(0.054)	(0.055)	(0.055)	(0.055)
Smoking, and alcohol or drug dependence	-0.110	0.077	0.076	-0.093	0.076	0.075
	(0.039)	(0.029)	(0.029)	(0.041)	(0.031)	(0.031)
Diabetes	0.393	0.487	0.487	0.418	0.512	0.511
	(0.032)	(0.029)	(0.029)	(0.034)	(0.031)	(0.031)
Heart diseases	0.145	0.171	0.171	0.123	0.150	0.149
	(0.064)	(0.061)	(0.061)	(0.068)	(0.066)	(0.066)
Antepartum fetal distress	1.803	1.995	1.996	1.798	1.973	1.974
	(0.140)	(0.123)	(0.123)	(0.138)	(0.127)	(0.127)
Obesity	0.717	0.849	0.850	0.751	0.880	0.881
	(0.048)	(0.048)	(0.048)	(0.051)	(0.050)	(0.050)
Anemia	0.409	0.530	0.531	0.407	0.535	0.535
	(0.042)	(0.039)	(0.039)	(0.044)	(0.041)	(0.041)
Malnutrition or insufficient prenatal care	-0.544	-0.461	-0.462	-0.491	-0.410	-0.411
	(0.051)	(0.049)	(0.049)	(0.053)	(0.052)	(0.052)
Fetal abnormality	0.295	0.464	0.464	0.416	0.560	0.560
	(0.093)	(0.071)	(0.070)	(0.087)	(0.069)	(0.069)
Polyhydramnios or oligohydramnios	0.655	0.734	0.734	0.660	0.743	0.743
	(0.051)	(0.043)	(0.043)	(0.054)	(0.047)	(0.047)
Asthma	-0.025	0.070	0.069	-0.045	0.040	0.039
	(0.048)	(0.045)	(0.045)	(0.051)	(0.048)	(0.048)
Isoimmunization	-0.167	-0.100	-0.100	-0.178	-0.117	-0.117
	(0.050)	(0.046)	(0.046)	(0.056)	(0.053)	(0.053)
Infant size issues	1.682	1.750	1.750	1.725	1.805	1.805
	(0.056)	(0.053)	(0.053)	(0.059)	(0.054)	(0.054)
Premature rupture of the amniotic sac	0.193	0.256	0.256	0.330	0.385	0.386
	(0.050)	(0.048)	(0.048)	(0.052)	(0.050)	(0.050)
Twins or more	1.508	1.601	1.602	3.011	2.849	2.849
	(0.077)	(0.079)	(0.079)	(1.063)	(1.085)	(1.088)
Malposition or malpresentation of fetus	3.825	3.994	3.994	0.000	0.000	0.000
	(0.073)	(0.074)	(0.074)	(.)	(.)	(.)
Preterm	-0.073	-0.061	-0.061	0.718	0.735	0.756
	(0.033)	(0.031)	(0.031)	(1.018)	(0.994)	(1.001)
Other complications of pregnancy	0.079	0.220	0.220	0.144	0.271	0.271
	(0.063)	(0.066)	(0.066)	(0.069)	(0.071)	(0.071)
Blood disorders or issues	1.487	1.552	1.552	1.565	1.628	1.628
	(0.053)	(0.056)	(0.056)	(0.062)	(0.065)	(0.065)
Uterine size issues	0.510	0.513	0.514	0.452	0.448	0.449
	(0.051)	(0.051)	(0.051)	(0.053)	(0.052)	(0.052)
Physical abnormalities	0.779	0.895	0.895	0.830	0.933	0.933
	(0.042)	(0.037)	(0.037)	(0.043)	(0.039)	(0.039)
Physician, hospital, and time FEs		X	X		X	X
Pseudo R2	0.384	0.418	0.418	0.093	0.141	0.141
Observations	187,873	187,873	187,873	133,551	133,551	133,551

Notes: This table reports coefficient estimates from Logit regressions of the C-section indicator using patient-level data from 2007 to 2009. All regressions include patient covariates such as demographics, insurance type, weekend delivery, and clinical risk factors. Columns (2) and (5) additionally include physician, hospital, and year-quarter fixed effects. Columns (3) and (6) additionally include physician housing returns, which are calculated as cumulative returns since the time of purchase and are reversed in sign. Columns (1)–(3) include all patients; Columns (4)–(6) restricts the sample to low-risk patients. Standard errors, clustered at the physician level, are reported in parentheses.

Table A2. **Alternative Clustering of Standard Errors**

Panel A: All patients									
	Cluster at hospital			*Cluster at patient zip code*			*Cluster at physician zip code*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section
Physician housing return	2.379	1.953	0.426	2.379	1.953	0.426	2.379	1.953	0.426
	(1.102)	(0.746)	(1.056)	(0.950)	(0.729)	(0.849)	(1.021)	(0.704)	(0.879)
Patient covariates	X	X	X	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X	X	X	X
Mean (dep. var.)	40.19	9.23	30.96	40.19	9.23	30.96	40.19	9.23	30.96
Observations	187,873	187,873	187,873	187,873	187,873	187,873	187,873	187,873	187,873

Panel B: Low-risk patients									
	Cluster at hospital			*Cluster at patient zip code*			*Cluster at physician zip code*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section
Physician housing return	3.130	2.963	0.167	3.130	2.963	0.167	3.130	2.963	0.167
	(1.326)	(0.883)	(1.195)	(1.223)	(0.965)	(0.999)	(1.295)	(0.899)	(0.978)
Patient covariates	X	X	X	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X	X	X	X
Mean (dep. var.)	22.72	11.27	11.45	22.72	11.27	11.45	22.72	11.27	11.45
Observations	133,551	133,551	133,551	133,551	133,551	133,551	133,551	133,551	133,551

Note: This table reports results from patient-level regressions of C-section indicators 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. C-section indicators are scaled by 100. Columns (1)–(3) cluster standard errors at the hospital level; Columns (4)–(6) at the patient zip code level; Columns (7)–(9) at the physician zip code level. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. 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 A3. 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
rev_cumret	-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	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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
rev_cumret	-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	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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. 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 physician fixed effects, hospital$\times$year-quarter fixed effects, patient zip code$\times$year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. 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. 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	X	X	X
Hospital-year-quarter FE	X	X	X
Patient zip code-year-quarter FE	X	X	X
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	X	X	X
Hospital-year-quarter FE	X	X	X
Patient zip code-year-quarter FE	X	X	X
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 physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. 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. 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	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
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 as specified in Equation (2). 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) further includes 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 regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panel A reports results for all patients; Panel B restricts the sample to low-risk patients. Standard errors, clustered at the physician level, are reported in parentheses.

Table A6. 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	X	X	X	X
Physician FE	X	X	X	X
Hospital-year-quarter FE	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X
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	X	X	X	X
Physician FE	X	X	X	X
Hospital-year-quarter FE	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X
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 (scaled by 100), estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Columns (1)–(3) use alternative measures of physician housing shocks: 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 physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panel A reports results for all patients; Panel B restricts the sample to low-risk patients. Standard errors, clustered at the physician level, are reported in parentheses.

Table A7. Alternative Sample Specifications

Panel A: All patients

	Allow physicians' entries/exits			*Allow time-varying house portfolios*		
	(1)	(2)	(3)	(4)	(5)	(6)
	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section
Physician housing return	2.532	2.127	0.405	2.267	1.889	0.378
	(1.027)	(0.638)	(0.874)	(0.854)	(0.561)	(0.728)
Patient covariates	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
Mean (dep. var.)	39.97	9.18	30.79	40.21	9.25	30.97
Observations	193,202	193,202	193,202	184,331	184,331	184,331

Panel B: Low-risk patients

	Allow physicians' entries/exits			*Allow time-varying house portfolios*		
	(1)	(2)	(3)	(4)	(5)	(6)
	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section
Physician housing return	3.359	3.139	0.220	3.186	2.773	0.413
	(1.266)	(0.815)	(0.977)	(1.023)	(0.701)	(0.832)
Patient covariates	X	X	X	X	X	X
Physician FE	X	X	X	X	X	X
Hospital-year-quarter FE	X	X	X	X	X	X
Patient zip code-year-quarter FE	X	X	X	X	X	X
Mean (dep. var.)	22.59	11.20	11.39	22.74	11.28	11.46
Observations	137,467	137,467	137,467	131,040	131,040	131,040

Notes: This table reports results from patient-level regressions of C-section indicators 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. C-section indicators are scaled by 100. Columns (1)–(3) include 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). Columns (4)–(6) allow physicians' house holdings to be time-varying and track physician housing returns over time. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. 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 MS-DRG code in the following set: 370, 371, 765, 766, 372, 373, 374, 375, 767, 768, 774, and 775. Among these, MS-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."

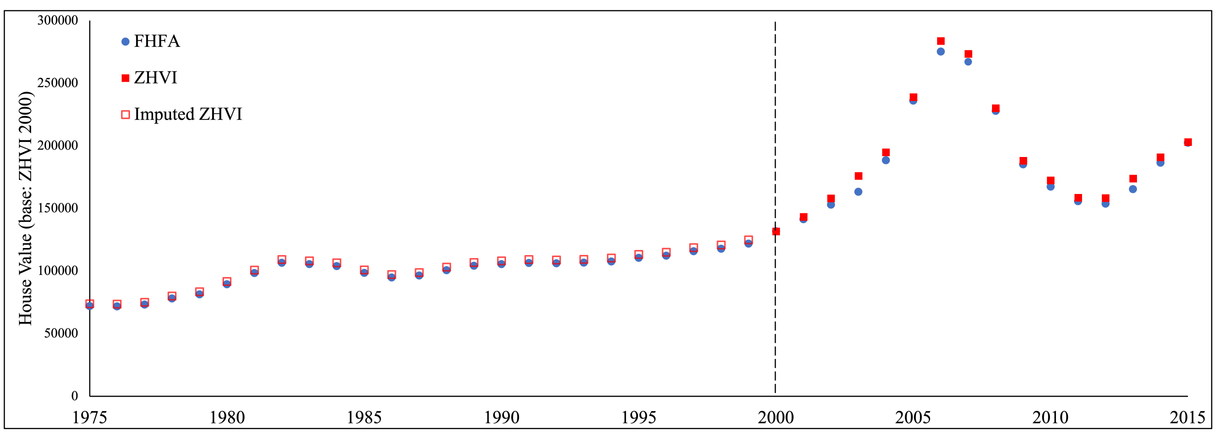
I construct physicians' housing portfolios step by step. First, I exclude house transactions that lack key information, including property ID, property location zip code, transaction date, and sales amount. I then collapse the transaction-level data to the physician×house×date level. To achieve this, 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 Price Index. 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: $\gamma = \frac{1}{T}\sum_{2000\leq t\leq T}^{T} \frac{HPI_t^{\text{ZHVI}}}{HPI_t^{\text{FHFA}}}$. 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