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 for identification. In the context of childbirth where physicians have discretion and financial incentives to adopt C-sections over vaginal deliveries, I find that a one-standard-deviation decline in physician housing returns increases C-section rates by 1.9 percentage points, or 7.6 percent. However, patient health outcomes are not substantially affected. Evidence suggests financial distress as the primary mechanism behind this behavioral response.

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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.

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

This paper studies how physicians' financial health influences their treatment choices and the implications for patient outcomes. Prior research on physician financial incentives has relied on changes in reimbursement rates induced by policy reforms where physicians' responses combine the income effect with the substitution effect (e.g., 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 as a natural experiment, which represents a substantial shock to physicians' financial health, given that households with incomes comparable to physicians typically hold around 20% of their wealth in real estate (Survey of Consumer Finance, 2009).

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

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

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

For the empirical analysis, I construct a time-varying, physician-level measure of cumulative housing returns, calculated as the change in average house values in the physician's zip code from the time of purchase to the time of treatment. Existing studies in household finance have used similar measures to proxy for households' wealth shocks and financial distress (Gerardi et al., 2018; Dimmock et al., 2021). I assume that physicians made their house-purchasing decisions prior to the financial crisis, which they could not have anticipated, so their subsequent housing returns are unlikely to correlate with potential treatment choices and patient outcomes 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.

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×time fixed effects to account for potential parallel responses at the hospital level. Second, housing wealth shocks to physicians may correlate with those faced by their patients, potentially affecting healthcare utilization (Acemoglu et al., 2013; Tran et al., 2023) and underlying health status (McInerney et al., 2013; Schwandt, 2018). To rule out such demand-side channels, I further control for patient zip code×time fixed effects in the regression. In a balance test, I show that physicians' housing returns are independent of observed patient characteristics after conditioning on these fixed effects.

As the main result, I find that a one-standard-deviation decrease in physicians' housing returns leads to a 1.9 percentage-point increase in the probability of C-section, which represents a 7.6% increase relative to the average C-section rate. This effect is economically meaningful and comparable to that of increasing the physician fee differential between C-sections and vaginal deliveries by about $300 (Gruber et al., 1999; Alexander, 2017; Foo et al., 2017), or that of increasing OB-GYN density by 32% (Gruber and Owings, 1996). In a placebo test on physicians who are most likely non-homeowners, I find no significant effect of pseudo housing returns on their C-section rates. I also estimate the dynamic effects on C-section rates using an event-study design. Physicians more affected by the real estate shock do not behave differently from those less affected in the pre-crisis period, lending support to the parallel-trends assumption. Physicians' responses become significant in 2008 and last until the housing market recovers.

I further show that the main results are insensitive to a series of extended fixed effects that are intended to capture more granular selection channels. The results also survive controlling for time-varying, physician-level confounding factors such as tenure, gender, and medical school ranking, as well as contemporaneous income shocks induced by fertility declines. Finally, the results are robust to a host of alternative sample and model specifications as well as alternative measures of physician housing returns.

The average effect documented before could mask substantial heterogeneity. In fact, non-Hispanic Black patients are more than twice as likely to receive C-sections than other patient groups when their physicians experience a negative financial shock, which suggests that racial disparities in healthcare may widen in economic downturns. I also find that patients whose expected medical benefits from C-section and vaginal delivery are similar are more likely to be affected. Effects also vary across physicians—junior and female physicians are more responsive to worse financial health.

As additional results, I find increases in both scheduled and unscheduled C-sections. I also consider two assisted methods used during attempted vaginal deliveries—induction and vacuum/forceps. There is no evidence for reduced use of these ancillary procedures, indicating that physicians are not substituting C-sections for these less invasive options. One might also wonder if physicians increase the overall treatment intensity during the hospital stay. I find that there is indeed an increase, as proxied by hospital charges, but it appears to be largely explained by the difference in costs between C-sections and vaginal deliveries. Lastly, I find no significant responses along the extensive margins such as the number of deliveries or patient composition.

A natural follow-up question is whether the increase in C-section use has any material impact on patient health. I focus on two sets of maternal outcomes—length of stay and complications occurring during or shortly after childbirth (e.g., hemorrhage, infection, laceration, and other severe morbidities). Patients' length of stay increases on average as a result of higher C-section rates, which is mainly explained by longer post-delivery stay. However, I find no significant changes in the incidence of complications. Taken together, these findings suggest that patient health is not substantially affected, at least for the metrics considered in this paper.

Housing shocks can trigger behavioral responses through multiple mechanisms. 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. Alternatively, shrinking home equity and tighter liquidity constraints may limit physicians' financial flexibility and create financial distress, in which case physicians may be motivated to recoup losses and avoid further costs, such as those of loan default, mortgage foreclosure, or even personal bankruptcy. I provide two sets of results in support of financial distress being the primary mechanism driving the behavioral responses: physicians only respond to negative housing shocks but not positive shocks, and responses are stronger among physicians under greater liquidity constraints—as proxied by higher Loan-to-Value (LTV) ratios.

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

More broadly, this paper adds to the literature on the real effects of household financial distress. Previous studies have shown that housing wealth shocks influence a wide range of household decisions, including but not limited to consumption (Mian et al., 2013), labor supply (Bernstein, 2021), fertility (Lovenheim and Mumford, 2013), education (Lovenheim, 2011), and political participation (McCartney, 2021). Financial distress has also been shown to affect workplace 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, creating externalities on patients and payers. Importantly, the inpatient-level healthcare data allow me to control for rich characteristics of the downstream consumers, which is often not available 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

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

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

the real estate market can have spillover effects on public health by changing physician behavior.

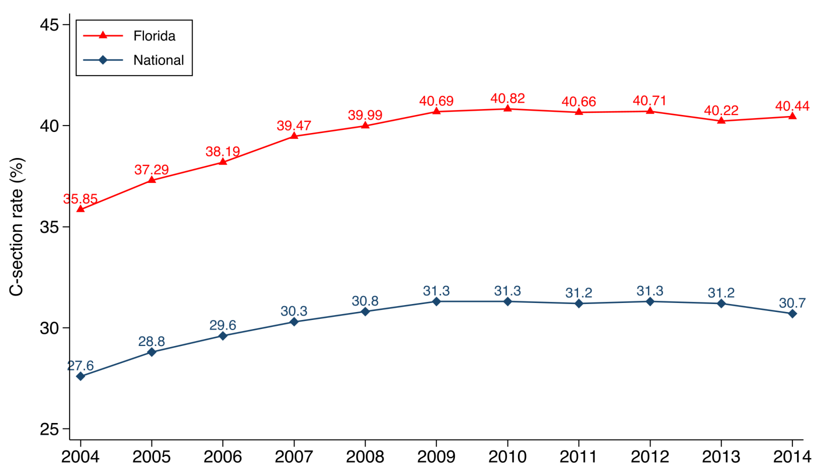
Finally, this paper advances the healthcare literature on physician-induced demand, particularly in the context of childbirth. Prior work has uncovered financial incentives (Gruber and Owings, 1996; Gruber et al., 1999), malpractice pressures (Dranove and Watanabe, 2010), information asymmetry (Johnson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

The remainder of the paper proceeds as follows. Section II describes the clinical setting. Section III introduces the empirical design. Sections IV and V report the empirical results. Section VI discusses potential mechanisms. Finally, Section VII concludes.

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 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 twice 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). As is shown in Figure 1, Florida's C-section rate is about 30% higher than the national average and among the highest in the U.S.

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



Notes: This figure shows C-section rates among singleton births in the U.S. and Florida from 2004 to 2014. National rates are sourced from the CDC's Natality Database. Florida rates are calculated using hospital inpatient data from the Florida Agency for Health Care Administration (AHCA).

Clinically, 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.[4] Patients without well-defined medical indications will attempt vaginal delivery, sometimes with labor induction. If complications such as "fetal distress" or "failure to progress" arise during labor, the physician may advise a (unscheduled) C-section. The diagnosis of these complications and the decision of delivery method often fall into a clinical gray area and depend heavily on physicians' training, judgment, and preferences. 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 patients from the uncertainties of prolonged and difficult labor. On the other hand, although rarely leading to maternal mortality, C-sections may result in maternal morbidity, including adverse events such as infection, hemorrhage, and blood clots 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 negatively affect infants as well, causing injuries during delivery and increasing the risk of future respiratory and immune system issues.[5] The potential overuse of C-sections, especially for low-risk births, has therefore raised concerns. Public health agencies and policymakers have advocated for reducing unnecessary C-sections. For instance, the Department of Health and Human Services (HHS) has set a target C-section rate for low-risk women of 23.6% by 2030 under the Healthy People Initiative, representing a significant reduction from the most recent level.

Financial incentives are cited as a key driver behind the rising adoption of C-sections (Gruber et al., 1999; Johnson and Rehavi, 2016; Alexander, 2017). The average physician fee for C-sections was about one-third higher than that for vaginal deliveries in the late 1980s (Gruber and Owings, 1996). More recently, using data from MarketScan during 2004–2010, Corry et al. (2013) estimate that both commercial insurers and Medicaid pay 10%–20% higher professional service fees for C-sections than for vaginal deliveries.[6] C-sections are also considered as more time-efficient for physicians. Vaginal labor onset is stochastic and frequently occurs at night or on weekends, foreclosing other clinical work and limiting rest. In contrast, scheduled C-sections offer "convenience" and allow physicians to manage workload more efficiently (Keeler and Brodie, 1993). For cases where a trial of labor has lasted long enough, the physician needs to decide whether to proceed or switch to a C-section (Card et al., 2023). An immediate C-section usually takes 45–60 minutes

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

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

[6] More specifically, physician fees of C-sections and vaginal deliveries are \$3,350 and \$2,887 for commercial insurance, \$1,654 and \$1,445 for Medicaid. There are separate financial incentives at the hospital level as well. For example, commercial insurers (Medicaid) paid an average of \$9,933 and \$6,738 (\$4,358 and \$3,102) for cesarean and vaginal deliveries as facility fees, respectively.

from incision to closure (Cunningham et al., 2014). In contrast, continuing a vaginal delivery requires the physician to be on-call for an uncertain period of time.[7] Overall, the marginal time commitment for a vaginal delivery can be several times larger than that for a C-section.

In terms of medical expenditure, the majority of costs such as operating-room overhead, anesthesia, medical supplies, and surgical assistance are incurred by the hospital, not physicians. In terms of liability risks, failure to perform a timely C-section is a common allegation in malpractice suits and can result in multimillion-dollar settlements. C-sections are therefore often perceived as a form of defensive medicine intended to demonstrate that "everything possible was done" to prevent potential harm (Currie and MacLeod, 2008; Dranove and Watanabe, 2010). Physicians also pay malpractice insurance premiums, but these premiums are usually bundled at the obstetric-specialty level instead of being priced per procedure.

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

III Empirical Design

III.A Data Sources

For empirical analysis, I combine two sources of data. First, I use de-identified hospital inpatient discharge data (2004–2014) obtained from the Agency for Health Care Administration (AHCA) of Florida to measure physician behavior and patient outcomes. These data include patients insured by all payers and discharged by all hospitals in the state. For each inpatient discharge, the data provide basic patient demographics, including age, race and ethnicity, gender, as well as diagnoses and procedures via ICD codes. These data also allow me to observe a series of patient outcomes, such as length of stay, discharge status, and hospital charges.

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

[7] For instance, the ACOG clinical guidelines recommend waiting for 4–6 hours before a C-section becomes a justified call rather than a premature surgery (Cahill et al., 2024). Consistent with this, Tilden et al. (2022) show that among nulliparous women still in active labor after 6 hours, the median remaining active-labor time is approximately 5 additional hours, before adding a median pushing duration of 1 hour.

To measure physicians' real estate holdings, I rely on CoreLogic, a real estate database that tracks housing transactions across the United States based on county deed records. CoreLogic has good coverage of property transactions dating back to the mid-1990s and has been widely used in the finance literature (e.g., Bernstein et al., 2021; Aslan, 2022). For each deed record, CoreLogic reports the transaction date, sale price, property address, buyer and seller names, as well as mortgage information such as loan amount, mortgage term, and interest rate. To match physicians with their houses, I first restrict the sample to properties located in Florida and to property types in one of the following categories: single-family residence, condominium, commercial property, duplex, or apartment. I then identify physician-owned properties by matching buyer or seller names with physician names using the combination "Last Name + First Name + Middle Name Initial." Several precautions, such as excluding physicians with common names and those matched with too many properties, are taken to reduce matching errors. Appendix A provides additional details on the matching procedure.

III.B Sample Construction

To construct the analytic sample, I first extract hospital inpatient records for childbirth patients treated by medical doctors instead of nurses and midwives. I then drop inpatient observations with missing values in key variables or with non-Florida residence. To exclude atypical cases, I also restrict the sample to patients aged 18 to 50 with a length of stay of no more than seven days.

Consistent with the healthcare literature studying provider behavior in childbirth (e.g., La Forgia, 2022), I then focus on a subset of low-risk patients, who are mothers with singleton births and no prior C-sections. The same criteria are also cited in the guidelines of the Agency for Healthcare Research and Quality (AHRQ, 2020). In my data, low-risk patients account for about 80% of all childbirths; the C-section rate among these patients is about 25%. Subsetting to these more standardized cases, where vaginal delivery is generally the default option, gives me a cleaner setting to examine the role of physician discretion in treatment choices.

I also apply several filters on the physician side. I first drop patients whose physicians either never or always performed C-sections, as well as those whose attending physicians differ from their operating physicians. This step ensures that the analysis focuses on physicians capable of performing C-sections themselves, rather than having to rely on external surgeons. I then restrict the sample to physicians who practiced continuously throughout the study period and exclude inactive physicians whose average quarterly delivery volumes are in the bottom percentile. Finally, I drop physicians with dubious house matches from CoreLogic. Appendix Table A3 summarizes these sample construction steps and the attrition at each step.

Table 1 presents descriptive statistics for both the primary sample of matched physicians and the holdout sample of unmatched physicians. There are 424 physicians with at least one property conceivably matched from CoreLogic by the end of 2006; they are defined as "homeowners" and included in the primary analyses. The other 334 physicians most likely rented homes, lived with family members during the sample period, or purchased their homes only after the crisis begins.

I group them as "non-homeowners" and use them in a placebo test later.[8]

Panel A of Table 1 shows that these two groups of physicians are fairly similar in terms of the patients they treat, regardless of patient demographics or risk factors. Panel B of Table 1 further shows that they are also similar in terms of gender, tenure, workload, and C-section use. Regarding house characteristics, it is not uncommon for a matched physician to own multiple properties. By the end of 2006, 73% of the matched physicians owned one house, 20% owned two, and 7% owned three. 71% of all physicians have their primary houses in the same three-digit zip codes as their main hospitals, and 72% have their primary houses in the same three-digit zip codes where most of their patients reside. On average, physicians in the sample purchased their homes for about $556,000 (in 2006 constant dollars) and had owned them for 4.8 years by the end of 2006.

III.C Physician Financial Shocks

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 losses for homeowner physicians, weakening their financial standing. To capture this real estate shock, I follow the household finance literature and measure physicians' cumulative housing returns since the time of purchase. Specifically, for a physician j who purchased a home in zip code z at time t_0, their cumulative housing return at a later time t is defined as $R_{j,t} = \frac{HV_{j,t} - HV_{j,t_0}}{HV_{j,t_0}}$, where $HV_{j,t}$ denotes the house value at time t.

Because CoreLogic does not document a property's market value after purchase unless it is resold—and repeat sales are rare in the data—I proxy the value of a house using the Zillow Home Value Index (ZHVI) for its zip code z at time t, denoted $ZHVI_{z,t}$.[9] If a physician owns multiple homes, let $\mathbf{Z}_j$ represent the set of zip codes where their houses are located. I then compute a weighted average housing return as in Equation (1) below.

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

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 throughout the sample period. The weight ϕ_z reflects the share of a 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 50% indicates that a physician has earned 50% as premiums and an $R_{j,t}$ of -50% indicates that a physician has lost 50% of their home's value, scaled

[8] The final match rate at the physician level is about 56%, comparable to that in Bernstein et al. (2021), which uses a similar method to identify the residences of patent applicants. This ratio is also broadly consistent with the homeownership rate among households of age 35–64 reported by the American Community Survey (ACS 5-year, 2008-2012).

[9] 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 A provides details of this imputation.

Table 1. Summary Statistics

Sample	*Unmatched physicians*		*Matched physicians*	
	Mean	SD	Mean	SD
Panel A: Patient-level variables				
Individual characteristics				
Age	27.502	[5.912]	27.729	[5.873]
Non-hispanic white	0.486	[0.500]	0.500	[0.500]
Non-hispanic Black	0.202	[0.402]	0.212	[0.409]
Hispanic	0.234	[0.423]	0.209	[0.407]
Medicaid	0.501	[0.500]	0.451	[0.498]
Commercial	0.421	[0.494]	0.473	[0.499]
Weekend delivery	0.190	[0.393]	0.191	[0.393]
35 years of age or older	0.138	[0.345]	0.142	[0.349]
Malposition or malpresentation of fetus	0.040	[0.196]	0.040	[0.195]
Preterm	0.058	[0.234]	0.058	[0.234]
Asthma	0.026	[0.158]	0.024	[0.152]
Polyhydramnios or oligohydramnios	0.037	[0.188]	0.035	[0.183]
Physical abnormalities	0.051	[0.220]	0.049	[0.215]
Blood disorders or issues	0.023	[0.151]	0.023	[0.151]
Uterine size issues	0.227	[0.419]	0.226	[0.418]
Infant size issues	0.063	[0.243]	0.065	[0.246]
Obesity	0.021	[0.143]	0.018	[0.134]
Anemia	0.079	[0.269]	0.080	[0.272]
Malnutrition or insufficient prenatal care	0.243	[0.429]	0.240	[0.427]
Diabetes	0.058	[0.233]	0.055	[0.228]
Smoking, and alcohol or drug dependence	0.061	[0.239]	0.055	[0.227]
Infectious and parasitic conditions	0.034	[0.181]	0.031	[0.174]
Heart diseases	0.010	[0.097]	0.009	[0.097]
Fetal abnormality	0.015	[0.120]	0.013	[0.115]
Antepartum fetal distress	0.004	[0.064]	0.004	[0.064]
Hypertension	0.085	[0.279]	0.084	[0.277]
Isoimmunization	0.021	[0.143]	0.024	[0.153]
Premature rupture of the amniotic sac	0.033	[0.180]	0.032	[0.177]
Other complications of pregnancy	0.019	[0.137]	0.016	[0.127]
Treatment				
C-section rate (%)	25.275	[43.459]	25.140	[43.382]
Unscheduled C-section rate (%)	10.857	[31.110]	10.668	[30.870]
# Observations	332,161		439,141	
Panel B: Physician-level variables				
Female	0.596	[0.491]	0.564	[0.497]
Tenure (as of 2006)	18.386	[9.619]	17.288	[8.496]
Number of deliveries per quarter	40.803	[24.969]	40.207	[23.842]
C-section rate (%)	26.928	[12.084]	26.692	[9.892]
Number of houses (as of 2006)			1.335	[0.596]
Occupancy (in years, as of 2006)			4.757	[4.270]
Purchase price of houses (in 2006 dollar)			555853.297	[397611.779]
# Observations	334		424	

Notes: This table presents descriptive statistics for the analytic sample of matched physicians and the holdout sample of unmatched physicians, covering the time period from 2004 to 2014. Panel A reports patient-level variables, including demographics and risk factors, as well as treatment. Panel B presents physician-level variables, including physician demographics and house characteristics (available only for matched physicians).

by the purchase price. This measure has several advantages. First, behavioral economists have emphasized the purchase price as a salient benchmark for homeowners (Genesove and Mayer, 2001) and physicians have been shown to have similar preferences (Rizzo and Blumenthal, 1996; Rizzo and Zeckhauser, 2003). Second, cumulative returns are strong predictors of negative home equity, offering insight into the potential channel through which financial distress may arise for physicians (Gerardi et al., 2018; Dimmock et al., 2021).

Importantly, cumulative returns capture a physician's exposure to real estate shocks by incorporating two physician-specific sources of heterogeneity. The first stems from the zip code(s) where physician j resides ($\mathbf{Z}_j$). Physicians' homes are scattered across different zip codes that exhibit heterogeneous housing price trends, even within the same recession period (Bogin et al., 2019). Physicians residing in more adversely affected zip codes experience larger depreciations in their real estate assets.[10] The second source of heterogeneity arises from the timing of home purchases (t_0). Physicians who bought homes earlier have accumulated more equity by paying down their mortgages and therefore have more "skin in the game" than those who purchased later at higher prices with less equity.[11] Combining these two dimensions of physician-level heterogeneity, $R_{j,t}$ is less likely to be confounded by unobserved factors that simultaneously influence patient demand, compared to market-level indicators of house price movement. I further elaborate the assumptions and tests for this argument later alongside the econometric specification.

The analytic sample spans from 2004 to 2014, covering the Great Recession as well as pre- and post-crisis years. Figure 2 summarizes the distribution of $R_{j,t}$ across physicians and over time. For the median physician, the cumulative housing return reached about 90% by the last quarter of 2006, suggesting that house value had almost doubled relative to purchase price. 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. The majority of these gains were completely wiped out by the end of 2012 for the median physician, which underscores the severity of this housing wealth shock.

III.D Econometric Specification

The empirical analysis is centered around the following two-way fixed effects regression design.

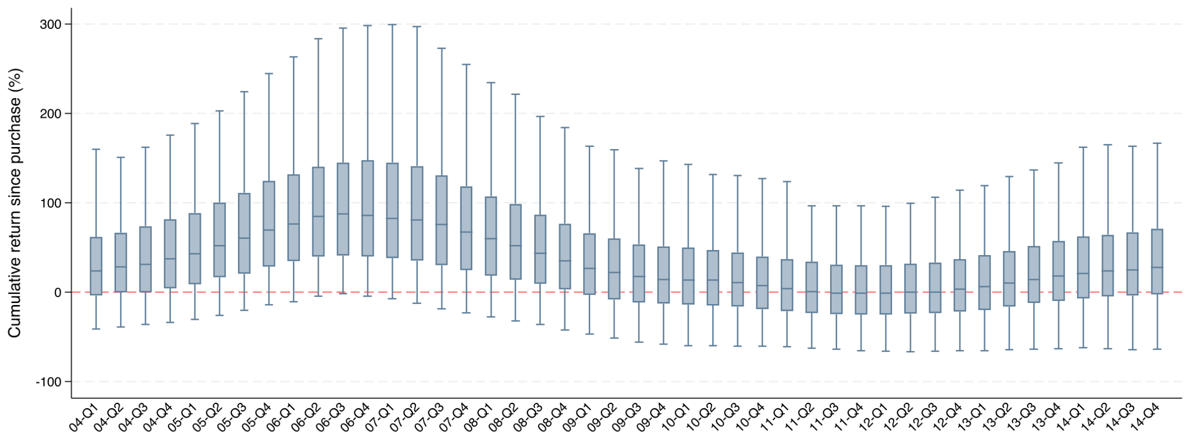
$$y_{i,j,h,c,t} = \beta \times R_{j,t} + \mathbf{X}_i\gamma + \mu_j + \delta_{h,t} + \eta_{c,t} + \varepsilon_{i,j,h,c,t} \tag{2}$$

Subscripts i, j, h, c, and t denote patient, physician, hospital, patient's zip code, and time (calendar year-quarter of childbirth), respectively. On the left-hand side of Equation (2), $y_{i,j,h,c,t}$ represents the main outcome variable of interest, a binary indicator (scaled by 100) for whether

[10] Appendix Figure B1 maps the number of physicians residing in each Florida zip code. Appendix Figure B2 shows the variation in $ZHVI$ percentage changes across zip codes during the crisis.

[11] Appendix Figure B3 displays the distribution of purchase years in the sample. Appendix Figure B4 highlights the implication of different purchase timing by showing that physicians' cumulative returns would have declined more sharply had they purchased their homes in an earlier year rather than later.

Figure 2. Distribution of Physician Housing Returns



Notes: This figure shows the distribution of physicians' housing returns for each quarter from 2004 to 2014. Housing returns are calculated as cumulative returns since the time of purchase and expressed in percentage points. 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.

patient i receives a C-section as opposed to a vaginal delivery. On the right-hand side, the key explanatory variable is physician housing return, $R_{j,t}$, as defined in Equation (1). In later analysis, I also expand $R_{j,t}$ to a host of event-study indicators to visualize the dynamic effects over time.

Equation (2) also controls for a comprehensive set of patient characteristics, $\mathbf{X}_i$, including demographics, insurance type, weekend delivery status, and clinical risk factors observed before labor (e.g., advanced maternal age, malposition of fetus, etc). These risk factors help adjust for the medical appropriateness of procedures, ensuring that the analysis compares treatment choices among clinically similar patients. Summary statistics for these covariates are reported in Table 1.[12]

Physicians may differ in their skills—some may be more proficient at performing C-sections or at diagnosing patients who need C-sections (Epstein and Nicholson, 2009; Currie and MacLeod, 2017). Therefore, Equation (2) includes physician fixed effects, μ_j, to capture such persistent differences in practice styles and preferences. One might also worry that physicians with certain unobserved characteristics systematically sort into areas that experienced steeper house price declines or tend to purchase their homes around the same time. Physician fixed effects address these concerns by accounting for physicians' housing portfolios (including both the choice of location and the time of purchase), which are fixed at the end of 2006 by construction. The identification of β therefore relies on within-physician variation in housing returns over time.

Finally, I include two sets of fixed effects to alleviate 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; Robinson et al., 2024), and found that hospital practices are sensitive to financial shocks (Dranove et al., 2017; Adelino et al.,

[12]Similar risk factors are also used by previous studies (Gregory et al., 2002; Johnson and Rehavi, 2016; Currie and MacLeod, 2017; La Forgia, 2022). Appendix Table B1 shows that most of them are strong predictors of C-section use.

2022). If physicians who experience larger wealth shocks are disproportionately influenced by hospital-level incentives, the estimate of β may be biased. To address this, I include hospital$\times$year-quarter fixed effects, $\delta_{h,t}$, which helps to isolate supply-side responses at the individual physician level from those at the facility level.

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

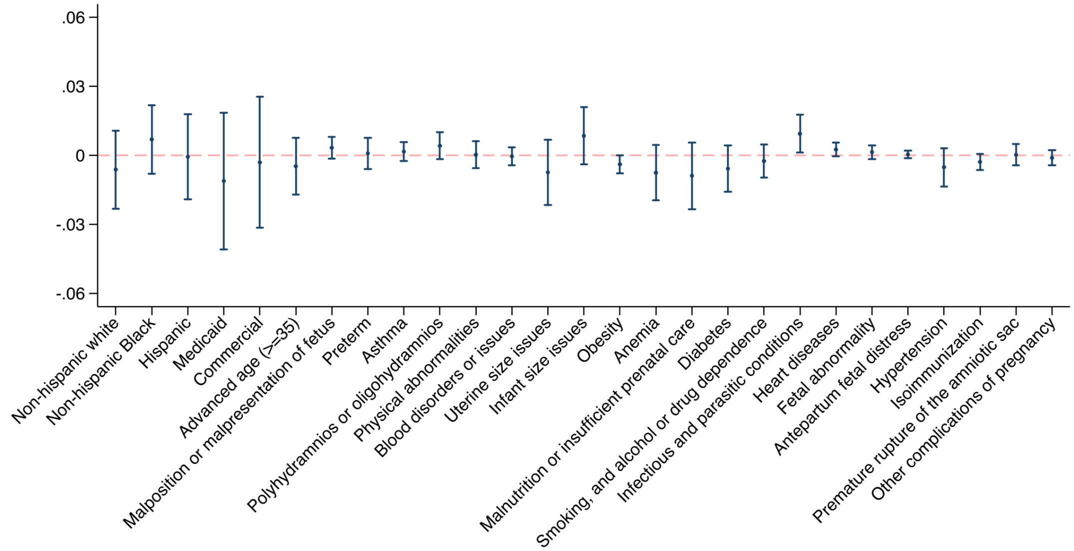
Finally, for much of the analysis unless otherwise noted, I estimate Equation (2) using patient-level data from 2004 to 2014 and a linear probability model to allow inclusion of high-dimensional fixed effects. Standard errors are clustered at the physician level for the main results and robust to being clustered at alternative levels (e.g., hospital, patient zip code, and physician zip code).

Identification. — The identification of β relies on the conditional independence assumption. That is, conditional on patient covariates and fixed effects at the physician, hospital$\times$year-quarter, and patient zip code$\times$year-quarter levels, potential patient treatments are mean independent of physician housing returns. In other words, patients paired with different physicians should not systematically differ in their observed characteristics after controlling for these covariates and fixed effects. I assess this assumption by testing whether patient covariates are balanced across physician real estate shocks. Specifically, I regress each of the patient characteristics on physician housing return, including the fixed effects controlled for in Equation (2). Figure 3 presents the estimated coefficients for physician housing returns from these individual regressions—they are generally close to zero and statistically insignificant at the 5% level.[13] A joint test on these risk factors produces an F-statistic of 1.5, failing to reject the null hypothesis that coefficients on patient characteristics are jointly zero.

The identification also requires that other unobserved physician characteristics that may affect patient treatments are conditionally mean-independent of physician housing returns (i.e., the exclusion restriction). This assumption could be violated if physicians with certain characteristics end up performing more C-sections over time while also involuntarily being exposed to disproportionately greater shocks. For example, younger physicians who tend to buy homes later may become more proficient at diagnosing patient conditions and rely less on C-sections as they gain experience. It is worth noting that the inclusion of physician fixed effects alongside year-quarter fixed effects already absorbs time-varying physician characteristics that evolve *linearly* over time,

[13]The only exception is "infections and parasitic conditions."

Figure 3. Balance Test for Patient Characteristics



Notes: This figure presents the results of the balance test. The sample covers the period of 2004–2014. Coefficient estimates and 95% confidence intervals from separate regressions of patient characteristics on physician housing returns (reversed in sign) are reported. Patient characteristics include patient demographics and risk factors. Physician housing returns are calculated as cumulative returns since the time of purchase. All regressions include fixed effects as in the baseline specification. Standard errors are clustered at the physician level.

such as age or years of experience, even if they are not explicitly included in the model. I also show that additionally controlling for *nonlinear* effects of physician characteristics (e.g., tenure, gender, and medical school training) does not affect the results.

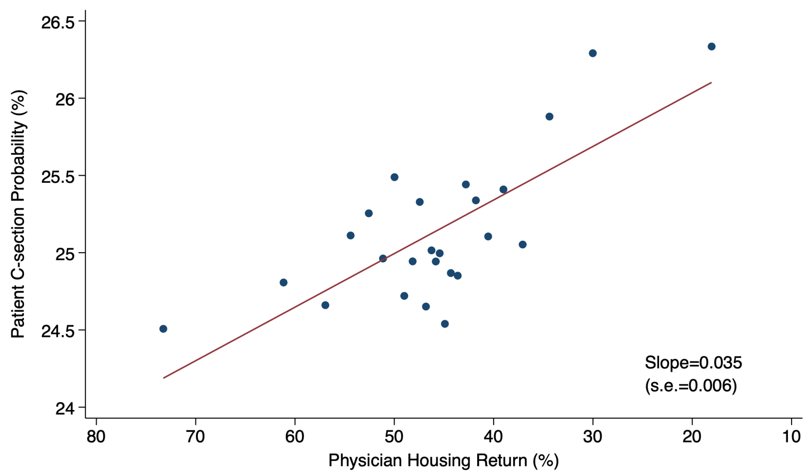
Finally, it is unlikely that physicians' housing decisions made *ex ante* are correlated with factors that influence patient treatment *ex post*. Although one might worry that physicians could have anticipated the housing crisis and made strategic investment or divestment decisions, prior studies such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

IV Effects on Treatment Choice

IV.A Main Results

Graphical Evidence. — Before delving into the regression analysis, I present a graphical relationship between physicians' housing returns and C-section rates. I first residualize both physicians' housing returns and C-section rates with respect to the fixed effects included in Equation (2). I then group the residualized observations into equal-sized bins based on housing return and compute the average C-section rate within each bin. Figure 4 visualizes this relationship using a binscatter plot. The fitted line shows that the C-section rate increases as physician housing return decreases, suggesting that physicians are more likely to perform C-sections when they experience greater losses in housing wealth.

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



Notes: This binscatter plot shows the relationship between C-section rates and physician housing returns using data from 2004 to 2014. Patients are grouped into 25 equal-sized bins based on their physicians' cumulative housing returns since purchase (expressed in percentage points), shown on the horizontal axis. The average C-section probability for each bin is plotted on the vertical axis. Both C-section probabilities and housing returns are residualized against the fixed effects included in the baseline specification. The red solid line represents a linear fit estimated over the binned averages.

Baseline Estimate. — Table 2 presents the regression results with the C-section rate (in percentage points) as the outcome. The key explanatory variable $R_{j,t}$ is reverse-coded so that a positive coefficient estimate reflects a higher C-section rate in response to negative housing shocks. Column (1) includes year-quarter and physician fixed effects. The coefficient on physician housing return is positive and statistically significant, indicating that greater financial losses by physicians are associated with a higher probability of C-section. Column (2) adds hospital$\times$year-quarter fixed effects to account for hospital-level incentives and responses. Column (3) adds patient zip code$\times$year-quarter fixed effects to account for time-varying local socio-economic conditions that could be both correlated with physicians' financial shocks and consequent to patients' underlying health. Finally, the preferred specification, Column (4), includes the full set of patient covariates. The estimate remains statistically significant and similar in magnitude. To put the estimate ($\hat{\beta}$=3.011) into perspective, a one-standard-deviation decrease in physicians' cumulative housing returns (0.64) leads to an increase of 1.9 percentage points in the overall C-section rate, which amounts to a 7.6% increase relative to the average (25.14 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 increasing the physician fee differential by about \$300.[14]

[14]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),

Table 2. **Effects on C-section Rate: Two-way Fixed Effects Model**

	C-section Rate				
	Baseline sample				Placebo
	(1)	(2)	(3)	(4)	(5)
Physician housing return	2.486	3.554	3.467	3.011	-0.127
	(0.832)	(0.846)	(0.857)	(0.799)	(0.396)
Year-quarter FE	✓				
Physician FE	✓	✓	✓	✓	✓
Hospital × year-quarter FE		✓	✓	✓	✓
Patient zip × year-quarter FE			✓	✓	✓
Patient covariates				✓	✓
Mean (dep. var.)	25.14	25.14	25.14	25.14	25.27
Observations	439,141	439,141	439,141	439,141	332,161

Notes: This table reports baseline results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2004 to 2014. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. The outcome variable is a binary indicator for C-section and scaled by 100. All columns control for physician fixed effects. Column (1) includes year-quarter and physician fixed effects. Column (2) additionally includes hospital×year-quarter fixed effects. Column (3) additionally includes patient zip code×year-quarter fixed effects. Column (4) additionally includes the full set of patient characteristics. Column (5) follows the same specification as in Column (4) and uses the placebo sample of unmatched physicians. Standard errors, clustered at the physician level, are reported in parentheses.

Gruber and Owings (1996) study the effect of OB-GYN density on C-section rates. Based on their estimate, the effect in my study is comparable to that of increasing the OB-GYN density by about 32%.[15] My result is also of similar magnitude to other estimates in the literature. For example, it is equivalent to about 90% of the gap in C-section rates between physician mothers and non-physician mothers (Johnson and Rehavi, 2016), and about 1.2 times the effect of OB-GYNs being acquired by physician practice management companies (La Forgia, 2022).

An alternative way to interpret the size of this effect is to benchmark physicians' gains from additional C-sections against their wealth losses. For example, consider the average physician whose cumulative housing return decreases by 90% over the 6-year period of 2007–2012. Using the baseline estimate in Table 2, a housing shock of this magnitude implies a 2.7 (=3.011×0.9) percentage-point increase in the C-section rate. Given that the average physician delivers about 161 births per year (see Table 1), this corresponds to roughly 26 more C-sections over the years. I then multiply the number of additional C-sections by the average physician fee gap between C-section and vaginal delivery to get the additional revenue (about $9,000).[16] Finally, given that the purchase price of the average physician's home in the sample is about $556,000, the total loss in

Alexander (2017) estimates that the C-section rate increases by 0.6 percentage points as the pay differential increases by $100. Using data from private insurers in California, Foo et al. (2017) also estimate that a $100 increase in the pay differential results in a 0.6 percentage point increase in the C-section rate. Based on these estimates, the 1.9 percentage-point effect I estimate is thus equivalent to the effect of increasing the pay differential by about $\frac{1.9}{(0.7+0.6)/2} \times \$100 \approx \$300$.

[15] Gruber and Owings (1996) estimate that a 10% increase in the OB-GYN density increases the probability of a C-section by 0.6 percentage points. Therefore, the 1.9 percentage-point effect I estimate is equivalent to the effect of increasing the OB-GYN density by about $\frac{1.9}{0.6} \times 10\% \approx 32\%$.

[16] Corry et al. (2013) estimate the fee gaps for commercially insured patients and Medicaid patients are $463 and $209, respectively. Given that these two groups of patients each account for approximately half of the sample, the average fee gap is $463×0.5+$209×0.5=$336. The additional revenue is therefore $336×26≈$9,000.

housing wealth is therefore on the order of \$500,000 (\$556,000×90%). In other words, the average physician could manage to recoup about 1.8% (=\$9,000/\$500,000) of the housing wealth loss by performing more C-sections. This is likely a lower bound of the actual gains given that the fee gap may not perfectly capture the non-pecuniary benefits of performing C-sections. For comparison, Gruber and Owings (1996) find that shifts to C-sections only offset 0.5% of physicians' negative income shocks. That said, the small ratio reveals that other constraints, such as institutional environment, patient preferences, and ethical considerations, can limit physicians' ability to further push on the C-section supply curve.

Placebo Test. — The primary analytic sample relies on housing shocks during the real estate crisis to identify the effect of physicians' financial health on their treatment choices. However, not all physicians were homeowners at the outbreak of the crisis. Non-homeowner physicians should arguably be insensitive to declines in housing values. In other words, if I were to run the same regression on a separate sample of non-homeowner physicians, I should expect a null effect.

To perform a placebo test on the non-homeowner physicians, I assign each of them a pseudo zip code and a pseudo purchase time. The pseudo zip code is imputed using the most common 5-digit physician zip code for every combination of physician tenure (5-year bins), gender (male or female), and hospital market (3-digit zip code) within the primary homeowner sample. The pseudo purchase time is imputed using the median purchase year-quarter for the same combination. I then compute pseudo housing returns for each of these physicians as if they had purchased a home in the pseudo zip code at the pseudo time. Column (5) of Table 2 reports the results of this placebo test. The estimate is close to zero and statistically insignificant, suggesting that non-homeowner physicians do not respond to pseudo housing shocks, providing additional support for the causal interpretation of the main results.

IV.B Dynamic Effects

Physicians more affected by negative housing shocks should not behave differently from those less affected absent the shocks. To test this parallel-trends assumption and to estimate the dynamic effects of real estate shocks on C-section rates, I supplement the baseline TWFE specification with the following event study design.

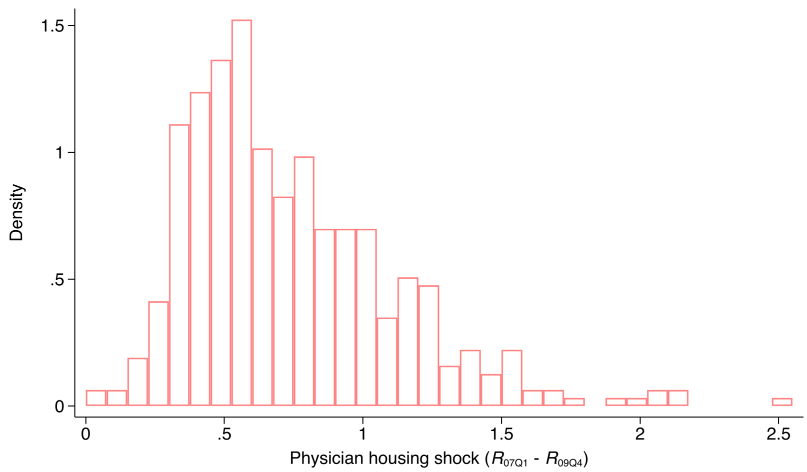
$$y_{i,j,h,c,t} = \sum_{\substack{2004 \leq t \leq 2014 \\ t \neq 2006}} \theta_t \times Shock_j + \mathbf{X}_i \gamma + \mu_j + \delta_{h,t} + \eta_{c,t} + \varepsilon_{i,j,h,c,t} \tag{3}$$

Equation (3) follows the specification of Equation (2) except that it fleshes out $R_{j,t}$ with a physician-level measure of their exposure to the housing shock, $Shock_j$, interacted with year indicators. To construct $Shock_j$ for a given physician, I take the difference in their cumulative housing returns between the beginning of the crisis (2007-Q1) and the peak of the crisis (2009-Q4): $Shock_j = R_{j,07q1} - R_{j,09q4}$.[17] The larger ("more positive") $Shock_j$ is, the greater ("more negative")

[17]Using Equation (1), it can be shown that $Shock_j = \sum_{z \in \mathbf{Z}_j} \phi_z (\frac{ZHVI_{z,07q1} - ZHVI_{z,09q4}}{ZHVI_{z,t_0}})$. In other words, $Shock_j$

the shock that a physician experiences. Figure 5 shows the distribution of this measure, which features rich across-physician variation. For instance, $Shock_j$ equals 0.65 for the median physician, meaning that they lost 65% of their housing values (scaled by the purchase price) during this period. At the same time, $Shock_j$ for the 25th- and the 75th-percentile physicians are 0.47 and 0.95, respectively.

Figure 5. Distribution of Physician Housing Shocks



Notes: This histogram shows the distribution of physician housing shocks over 2007–2009. The housing shock is calculated as the decline in cumulative housing returns from 2007-Q1 to 2009-Q4 for each physician.

Figure 6(a) visualizes the estimated coefficients ($\hat{\theta}_t$) from the event study regression of C-section rate. First, pre-crisis coefficients are close to zero and statistically insignificant. In other words, physician housing shocks over the course of 2007–2009 do not predict C-section rates in the pre-crisis period, providing support to the parallel-trends assumption. In fact, the trend remains flat until 2008 when the crisis starts to unfold. From 2008 on, $\hat{\theta}_t$ becomes significantly positive, suggesting that physicians with more negative shocks perform significantly more C-sections. Take the treatment effect in 2008 ($\hat{\theta}_{2008}$=3.004) as an example. It means that patients of a physician with one-standard-deviation more negative shock over 2007–2009 have a 1.14 (=3.004×0.38) percentage-point higher probability of receiving a C-section. Alternatively, the physician at the 75th percentile of the shock distribution tends to have a 1.44 (=3.004×0.48) percentage-point higher C-section rate than the physician at the 25th percentile of the shock distribution.

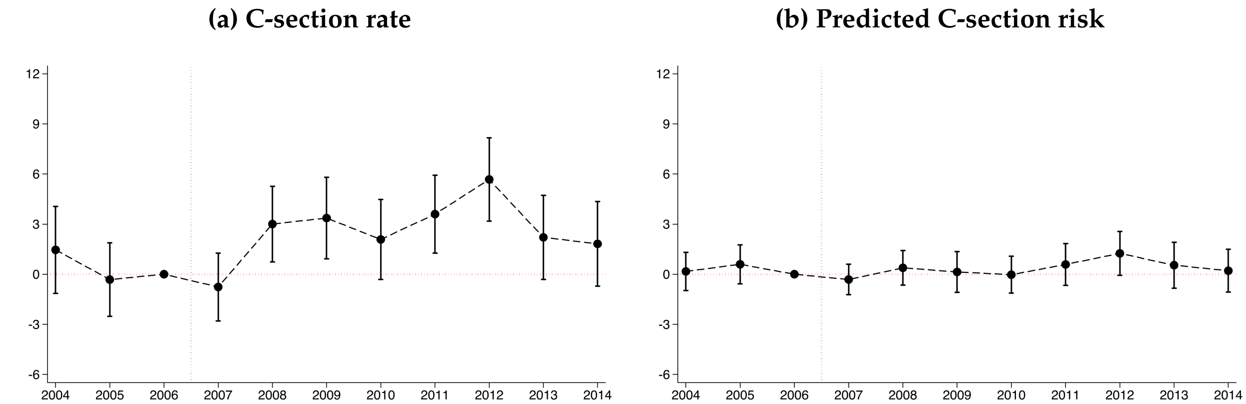
The treatment effects remain elevated after 2008 and until 2012, a period when physicians continue to experience house price declines. Physicians who have become accustomed to performing more C-sections may also lack incentives to revert to vaginal delivery. Finally, the effect shrinks in magnitude and becomes statistically less significant in 2013–2014, which is consistent with the fact that physician housing returns on average start to increase again in 2013.

To further rule out the possibility that the main results are driven by high-risk patients selecting into more affected physicians, I also study patient risk profile as an outcome. Specifically, I follow

captures the house value changes during the crisis as a percentage of the initial purchase price.

prior studies to predict each patient's "appropriateness" of receiving a C-section (or "C-section risk") by estimating a Logit regression of actual C-section use on patient demographics and risk factors (Currie and MacLeod, 2017; Robinson et al., 2024). To avoid potential selection, I include all patients in both the homeowner and non-homeowner samples in the prediction.[18] I then use the predicted value (scaled 0–100) as the outcome variable in the event study regression.[19] Figure 6(b) reports the results—patient risk does not differ between more affected and less affected physicians over time.

Figure 6. Dynamic Effects on C-section Rate and C-section Risk



Notes: These figures present the estimated coefficients from patient-level event-study regressions as specified in Equation (3). The sample spans 2004 to 2014. Panel (a) uses a binary indicator for C-section (scaled by 100) as the outcome variable and controls for patient covariates, as well as physician, hospital×year-quarter, and patient zip code×year-quarter fixed effects. Panel (b) uses the predicted C-section risk (scaled by 100) as the outcome variable and controls for the fixed effects but not patient covariates. Standard errors are clustered at the physician level.

Within the same event study framework, I also perform several robustness checks. First, I define physicians' exposure to housing shocks over a longer window (i.e., 2007–2012). Second, I consider using a binary indicator for more affected physicians (i.e., $Treated_j = \mathbf{1}\{Shock_j > p50\}$) to replace the continuous $Shock_j$ as an alternative treatment variable. Third, I consider using changes in house value for the zip code that the physician lives in to define their exposure to real estate shocks (i.e., $Shock_{z(j)} = \frac{ZHVI_{z(j),07q1} - ZHVI_{z(j),09q4}}{ZHVI_{z(j),07q1}}$). Results using these alternative treatment definitions are consistent with the preferred specification (see Appendix Figures C1(a) to C1(c)).

IV.C Additional Tests

Appendix Figure D1 summarizes results of several additional tests on top of the baseline specification. I begin by adding extended fixed effects to the baseline specification to rule out alternative selection channels. I then show that the effect of housing shocks is not confounded by the time-varying effect of some physician characteristics or contemporaneous income shocks induced by

[18] Appendix Table B1 reports the results from this Logit regression and Appendix Figure B5 shows the distribution of the predicted C-section risk.

[19] This regression excludes patient covariates from the right-hand side as they have been used to predict patients' C-section risk.

fertility declines. Finally, I consider a range of alternative sample and model specifications, as well as alternative measures of physician housing returns, all of which yield consistent results.

Other Selection Channels. — One might worry that patients with unobserved preferences selectively choose certain providers that are systematically more or less exposed to housing wealth shocks. I test whether the main results are robust to this more granular selection between patients and physicians in two ways: extended fixed effects and refined subsamples.

I first assess whether *patient-hospital* matching may be driving the main results. To do so, I 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. Alternatively, 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. These tests yield similar results.

Next, I consider the possibility of *patient-physician* matching. To examine this, I include patient zip code×physician fixed effects to control for time-invariant factors specific to each patient zip-physician pair. Alternatively, I focus on a subset of patients who live far from their physicians by requiring that the patient's 3-digit zip code differs from that of their physician. These patients are arguably less likely to have a prior relationship with their physicians or to possess any information about their physicians' financial health in advance. These tests also produce similar results.

Finally, *physician-hospital* matching may also play a role. Prior research has shown that physician performance can be hospital-specific and there is notable performance dispersion among physicians even within the same hospital (e.g., Mourot, 2025). The policy implication would differ if the estimate merely captures physicians reallocating C-sections across hospitals, rather than reflecting a shift in their practice styles. To address this concern, I include physician×hospital fixed effects in the regression. Alternatively, I restrict the sample to physicians who practice at only one hospital during the study period (i.e., "single-homing" physicians). In both cases, results are consistent with the baseline estimates.

Time-Varying Effects of Physician Characteristics. — Physician fixed effects included in the baseline specification help control for time-invariant physician characteristics such as practice styles and risk preferences. Any remaining threats to identification would need to be correlated with physician housing returns in a time-varying manner. Also, note that the year-quarter fixed effects absorb time-varying physician characteristics that evolve *linearly* over time, such as age or years of experience. The question is therefore whether the main results would survive controlling for such *non-linear* effects of physician characteristics.

The first physician characteristic I consider is tenure, which I measure as the number of years from medical school graduation to the focal year. One might suspect that, for example, the accumulation of experience may accelerate over time and thus confound the financial shocks that physicians face. I then additionally include physician tenure×year-quarter fixed effects in the baseline specification. It is also possible that physicians of different genders may face disproportionate financial shocks and develop different treatment patterns. I therefore add physician gender×year-quarter fixed effects in the regression as an additional check. Lastly, physicians with different medical school training may have different practice styles. I therefore include physician medical school ranking×year-quarter fixed effects.[20] Appendix Figure D1 shows that the main results hold despite controlling for these time-varying potential confounds.

Contemporaneous Shocks from Fertility Declines. — Besides substantial wealth losses from the housing market, physicians might have also experienced other financial shocks during the Great Recession. For example, Kearney et al. (2022) document a decline in U.S. fertility rates, which started in 2007. In Florida, the fertility rate decreased from 1.30 births per 100 population in 2006 to 1.11 in 2013—a non-trivial 14.6% decline.[21] As in Gruber and Owings (1996), fertility declines can lead to negative income shocks for OB-GYNs, which in turn induce them to increase treatment intensity by adopting more C-sections.

Although the main results in this paper should not be biased by the secular trend of fertility declines, it would be problematic if, for instance, physicians with more negative housing shocks happen to be more affected by declining fertility. To more explicitly address this concern, I construct a "shift-share"-style, time-varying measure of physicians' exposure to fertility shock. I first calculate the fertility rate for each zip code×year (i.e., the "shift"). Then, for each physician, I use pre-crisis data to calculate the percentage of their patients coming from each zip code (i.e., the "share"). Finally, I calculate a weighted average fertility rate for each physician×year by multiplying the shifts and the shares, which is meant to capture the physician-specific fertility shock over time after conditioning on physician and time fixed effects. The coefficient on physician housing returns remains similar to the baseline estimate after controlling for the fertility shock. In other words, any negative income shock that fertility declines might have caused is unlikely to explain away the effect of physician housing shocks during the same period.[22]

Other Robustness Checks. — I test the sensitivity of the main results with respect to three specifications that I adopt for the primary analytic sample. First, I have focused on low-risk patients with singleton births and no prior C-sections in the primary analytic sample. To test whether the result holds for a broader patient pool, I include all patients in the regression. Second, I have also focused 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. I therefore include physicians who entered the labor force after the recession began (i.e., late entries), as well as those who retired before the end of sample (i.e., early exits). Third, I have also fixed each physician's housing portfolio as of the end of 2006 when calculating their housing returns and assumed the portfolio is held throughout the sample period. However, some physicians may have purchased homes after the onset of the crisis or sold their properties before

[20]Following Schnell and Currie (2018), I use medical school rankings collected from the U.S. News and World Report.
[21]Numbers are calculated using annual vital statistics data from the Florida Department of Health.
[22]The coefficient on fertility shock has a small and insignificant effect on C-section rates ($\hat{\beta}$=−0.592, s.e.=3.879).

it ended. I therefore allow for varying homeownership over time and track physician housing returns accordingly. Fourth, I also report estimates with standard errors clustered at more conservative levels, including the hospital, patient zip code, and physician zip code. Results using these alternative sample and model specifications, as reported in Appendix Figure D1, remain similar to the baseline estimates.

Lastly, I consider several alternative measures of physician housing return. 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 as in the baseline estimate but *lagged by one quarter*. Second, physicians may place greater weight on more recent changes in house values. To capture this, I use the cumulative housing return over the past quarter (i.e., *quarter-over-quarter* return) as a measure of housing wealth shocks. I also extend the return window by constructing a *year-over-year* housing return. Appendix Figure D1 shows that these alternative measures give estimates consistent with the hypothesis.

IV.D Heterogeneity

To provide a more comprehensive picture of how physicians' financial health affects their treatment choices, I explore heterogeneity along two dimensions: patient characteristics and provider (including physician and hospital) characteristics. Results are summarized graphically in Figure 7 with estimated effects of a one-standard-deviation decrease in physician housing returns, as a percentage of the sample mean.

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

First, I divide the sample into four groups based on patient race and ethnicity: non-Hispanic Black, non-Hispanic white, Hispanic, and others. They account for 21.2%, 50.0%, 20.9%, and 7.9% of all cases, respectively. I then estimate separate regressions for each of these groups. The effect is the largest and the most statistically significant among non-Hispanic Black patients (12.9%), with the magnitude more than twice as large as that of non-Hispanic white patients (5.7%). Effects for Hispanic (6.1%) and other patients (5.6%) are smaller in magnitude and insignificant.

The larger treatment effect for Black patients may be because Black patients are treated by physicians who are more affected by the negative housing shocks, or because Black patients are riskier than non-Black patients. I test these possibilities but do not find any evidence (Appendix Table D1). Overall, these findings are consistent with recent studies showing that Black patients are more vulnerable to provider discretion. For instance, Singh and Venkataramani (2022) find that Black patients tend to wait longer, receive less care, and ultimately face higher mortality when hospitals approach capacity constraints. In a childbirth setting similar to mine, Corredor-

Waldron et al. (2024) document a racial gap in C-section rates between non-Hispanic Black and other patients, which disappears when the cost of unnecessary C-sections increases. My findings add to this body of literature by highlighting how racial disparity in healthcare may widen during periods of deteriorating physician financial health.

How physicians' financial shocks affect patient welfare also depends critically on whether the affected patients are appropriate candidates for C-sections. Intuitively, physicians are likely to have already performed C-sections on patients who stand to benefit the most, and may be less inclined to do so for those with minimal expected benefits even when facing greater financial incentives. In other words, patients with *medium*-level expected benefits should be more likely to receive C-sections at the margin. To test this prediction, I divide patients into three tertiles based on their predicted appropriateness for receiving a C-section as defined earlier in Section IV.B. Subsample regressions show that the effect is the largest and the most significant among patients in the medium-appropriateness group (10.2%), compared to those for the low-appropriateness group (6.7%) and the high-appropriateness group (4.1%).

This "hump-shaped" pattern suggests that patients more affected by physician discretion are those without clear benefits from C-sections. To confirm, I investigate the difference between the average patient and the marginal patient in the spirit of Gruber et al. (1999). Gruber et al. (1999) establishes that the change in the average outcome of a birth cohort is equal to the difference in outcomes between the marginal birth and the average birth. In my case, if the marginal patients are indeed good candidates for C-sections, moving them from vaginal delivery to C-section would lead to a higher average appropriateness score among the C-section births ex post. Appendix Table D2 reports the results of this test. Overall, the average appropriateness score of C-section births does not significantly change when the C-section rate increases. In other words, the marginal C-sections are likely *not* cases where C-sections are clearly favored.

Heterogeneity by Provider Characteristics. — The effect of physician financial health on physician treatment choices may vary across physicians and hospitals. I begin by investigating whether the effect on female physicians is different from that on male physicians. In my data, 56% of OB-GYNs are female, and they deliver about 51% of all births. Existing work has shown that female physicians are more likely to adopt less aggressive treatment options (Currie et al., 2016). Also, 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 (Greenwood et al., 2018; Cabral and Dillender, 2024). I find that patients are more likely to receive C-sections when their physicians are female, which suggests that gender concordance probably does not generate overwhelming benefits in my 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 (Pruckner et al., 2025).

I then study whether the effect of financial shocks on treatment choices varies by physician tenure. Physicians' tenures (i.e., how long they have practiced since graduating from medical school) are measured at the time of 2006. I group patients into two groups based on whether they are treated by junior or senior physicians. I find a larger and more significant effect among junior physicians. This pattern is consistent with the intuition that junior physicians are more likely to have higher outstanding debt and less accumulated personal wealth, and therefore more vulnerable when faced with negative wealth shocks.

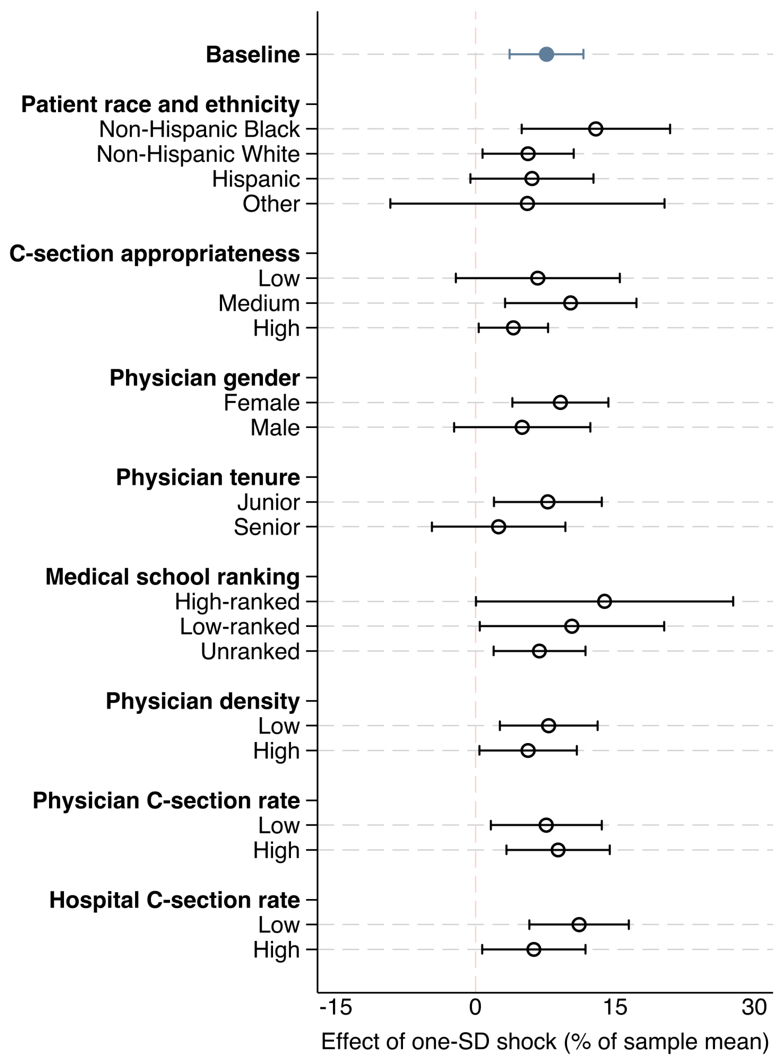
Next, I test whether medical school training affects physicians' responses. Prior studies such as Schnell and Currie (2018) have shown that physicians trained at top medical schools prescribe fewer opioids, highlighting the role of medical education in shaping physician practice styles. I divide physicians into three categories based on their medical school rankings on the U.S. News and World Report: (1) higher-ranked (ranking $<$ median among ranked schools), (2) lower-ranked (ranking $\geq$ median and $<$ 100), and (3) unranked.[23] I do not find significant differences in the effect of housing shocks across these three groups, which suggests that more elite medical training, by itself, should not be assumed to equip physicians with more sophisticated knowledge to cope with financial challenges.

I also examine whether physicians' responses vary 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, competition may discipline over-treatment or may have already pushed physicians close to the limit, leaving little room for adjustments even when they are more financially motivated. In a similar spirit of Gruber and Owings (1996) and Baicker et al. (2006), I proxy competition using physician density, defined as the number of OB-GYNs per birth in a county and measured as of 2006. Patients are then grouped based on whether they reside in lower-density or higher-density physician markets. I find that effects in both low-density and high-density markets are significant and have similar magnitudes.

Finally, I study how the estimated effect depends on both physicians' and hospitals' ex ante C-section rates. Prior studies have pointed out that physician practice styles are highly persistent (Epstein and Nicholson, 2009), and that physicians' treatment decisions tend to be auto-correlated 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 physician's *excessive* C-section rate as the difference between their actual C-section rate and their predicted rate aggregated across all of their patients seen prior to the crisis. Subsample regressions yield similar estimates for low-C-section-rate and high-C-section-rate physicians. However, when I measure excessive C-section rates at the hospital level, physicians' responses are slightly stronger in hospitals with lower ex ante C-section levels. This seems to imply that physicians face less institutional pressure to perform more C-sections in facilities where C-sections are less common, and therefore C-section rates across different hospitals may converge during times of negative financial shocks.

[23] In the analytic sample, 32% of medical schools are higher-ranked, which have trained 13% of physicians; 36% of medical schools are lower-ranked, which have trained 19% of physicians; and 33% of medical schools are unranked, which have trained 68% of physicians.

Figure 7. Heterogeneous Effects by Patient and Provider Characteristics



Notes: This figure shows the heterogeneous effects of physician housing returns on C-section rate by patient and provider characteristics from subsample regressions. Estimates are scaled as the effect of a one-standard-deviation decrease in physician housing returns, expressed as a percent of the subsample-specific average C-section rate. The blue top row reports the estimate from the baseline specification and black rows report subgroup estimates with 95% confidence intervals.

V Effects on Additional Outcomes

The main analysis so far has focused on the major treatment margin in childbirth—C-section versus vaginal delivery. This section explores the impacts on a number of additional outcomes, including other treatment margins and patient health.

V.A Other Treatment Margins

Do physicians adjust their treatment choices along other margins when facing negative financial shocks? I begin by examining differences in physicians' responses between scheduled and unscheduled C-section rates. C-sections can be scheduled before the onset of labor. Once labor begins, the clinical guidelines on when to discontinue labor are less clear and physicians may also recommend a (unscheduled) C-section if they believe the benefits of an immediate surgery outweigh the costs of continuing labor. Columns (1) and (2) of Table 3 use unscheduled and scheduled C-section rates as the outcome variables, respectively.[24] Lower physician housing returns significantly predict the incidence of both unscheduled C-sections and scheduled ones. The finding of higher unscheduled C-section rates suggests an important role of physician discretion in driving the results, as patients usually have limited abilities to challenge physicians' opinions in these cases. At the same time, higher scheduled C-section rates may reflect physicians' efforts to schedule more procedures.

Next, one might wonder whether the higher C-section rate is a result of physicians using fewer assisted methods during attempted vaginal deliveries. One such method is induction, which is used to stimulate uterine contraction and avoid a prolonged first stage of labor. Column (3) of Table 3 reports the results using an indicator for whether a patient received induction as the dependent variable. The estimate is negative but statistically insignificant.[25] Another example of assisted delivery involves the use of vacuum devices or forceps, which are considered ancillary procedures and typically used during the second stage of labor. If physicians are substituting C-sections for these less invasive procedures, one would expect a decline in their usage when physicians face negative financial shocks. However, Column (4) of Table 3 uses an indicator for vacuum/forceps as the outcome variable and finds no evidence that patients are less likely to receive such procedures.

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 use the total dollar amount of hospital charges as a summary measure of overall treatment intensity as in Johnson and Rehavi (2016). Column (5) of Table 3 presents the result using logged hospital charges as the dependent variable. Hospital charges

[24] Following Henry et al. (1995) and Gregory et al. (2002), I define unscheduled C-sections as those associated with ICD diagnosis codes indicating a trial of labor.

[25] Appendix Table D3 reports subsample results of other treatment margins by delivery mode. There is some evidence for physicians using induction less often among C-section births, consistent with the higher scheduled C-section rate.

significantly increase as physician housing returns decline. Specifically, a one-standard-deviation decrease in physician housing returns leads to a 1.2% increase in hospital charges, equivalent to a \$157 (=\$13,064$\times$1.2%) increase for the average patient. However, as shown in Appendix Table D3, this effect becomes statistically insignificant after conditioning on delivery mode, suggesting that the observed increase in hospital charges is largely explained by the margin of C-section versus vaginal delivery.

Lastly, I explore the effect on the number of deliveries and patient composition (i.e., extensive margins). 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 a physician$\times$year-quarter panel, controlling for physician and year-quarter fixed effects. Column (6) of Table 3 reports the result from a Poisson regression model. The estimate is statistically insignificant, and if anything, physicians treat slightly fewer patients.[26] Similarly, I calculate the share of Medicaid patients for each physician in each period. Financially shocked physicians may have incentives to treat more commercially insured patients who typically pay higher reimbursement rates. However, Column (7) of Table 3 shows that the payer mix does not significantly change in physician housing returns. These findings are perhaps not surprising given that patient volume and patient composition can be more affected by demand-side factors beyond physicians' control, such as demographic shifts and changing fertility rates.

Table 3. Effects on Other Treatment Margins

	Unscheduled C-section	*Scheduled C-section*	*Induction*	*Vacuum/ Forceps*	*Hospital charges*	*# of deliveries*	*% Medicaid patients*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Physician housing return	1.361	1.650	-0.827	0.668	0.012	-0.100	-0.640
	(0.543)	(0.589)	(0.740)	(0.460)	(0.008)	(0.072)	(1.543)
Year-quarter FE						✓	✓
Physician FE	✓	✓	✓	✓	✓	✓	✓
Hospital × year-quarter FE	✓	✓	✓	✓	✓		
Patient zip × year-quarter FE	✓	✓	✓	✓	✓		
Patient covariates	✓	✓	✓	✓	✓		
Mean (dep. var.)	10.67	14.49	20.01	4.55	9.33	41.22	36.87
Observations	439,141	439,141	439,141	439,141	439,141	17,575	17,575

Notes: This table reports results from regressions of other treatment margins on physician housing returns. The sample spans 2004 to 2014. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1)–(4) use binary indicators (scaled by 100) for unscheduled C-section, scheduled C-section, labor induction, and vacuum/forceps use as outcome variables, respectively. Column (5) uses logged hospital charges. Columns (1)–(5) include patient covariates and fixed effects as in the baseline specification. Column (6) presents results from a Poisson regression of physician-level delivery counts. Column (7) presents results from a regression of physician-level payer mix (% of patients with Medicaid coverage). Both Columns (6) and (7) control for year-quarter and physician fixed effects. Standard errors, clustered at the physician level, are reported in parentheses.

[26] Delivering physicians can also see patients throughout pregnancy, so their responses might translate into more deliveries after three quarters. However, I do not find evidence for more deliveries even accounting for the time lag.

V.B Patient Health

A natural follow-up question is whether changes in physician treatment choices translate into substantive differences in health outcomes. However, predictions regarding this issue are ambiguous ex ante. On the one hand, patient health may worsen if physicians' adoption of more profitable procedures results in over-treatment that deviates from the clinical optimum. On the other hand, financially distressed physicians may practice more conservatively and cautiously to avoid adverse outcomes. Meanwhile, as previously shown in Section IV.D, marginal patients most affected by these behavioral shifts are likely those who are indifferent between cesarean and vaginal deliveries. Because the relative benefits and risks of C-sections are less clear for this patient group, whether the increased use of C-sections leads to meaningful changes in health outcomes remains an empirical question.

I study two sets of maternal health outcomes. The first set concerns the time a patient stays in the hospital (from the date of admission to the date of discharge). I follow the baseline specification except for using the count of inpatient days as the dependent variable with a Poisson regression model. Column (1) of Table 4 reports the result: patients' length of stay tends to increase following physician financial shocks. Specifically, a one-standard-deviation decrease in physician housing returns leads to an increase of 1% (or 0.025 days) in length of stay, which is largely in line with findings in other research (e.g., Card et al., 2023).

To explore what drives the increase in length of stay, Columns (2) and (3) of Table 4 decompose the total stay into two components: pre-delivery stay (the number of days from admission to delivery) and post-delivery stay (the number of days from delivery to discharge). For the average patient, the total length of stay is 2.49 days, consisting of 0.35 days pre-delivery and 2.14 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.

Finally, I examine a range of complications that could occur during or after labor and delivery. Following prior studies (Johnson and Rehavi, 2016; Freedman and Hammarlund, 2019; La Forgia, 2022), I define four types of events using ICD codes: hemorrhage, infection, laceration, and severe maternal morbidity. The first two types, hemorrhage and infection, can occur in both cesarean and vaginal deliveries. The third type, laceration, is typically associated only with vaginal attempts. 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, about 6% of patients experience at least one of these complications.[27]

As shown in Columns (4) to (7) of Table 4, coefficients on physician housing return are all

[27] 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, in-hospital maternal mortality, is even more rarely observed in the Florida data, with a rate of approximately 4 per 100,000 patients. Given these data limitations, one should perhaps interpret the estimated health effect here as a conservative lower bound.

statistically insignificant. Overall, I do not find strong evidence that physicians' responses to negative financial shocks affect patient health substantially, at least for the four measures considered. Appendix Table D4 further shows results separately for C-section and vaginal births—maternal health does not significantly change in either subsample. That said, it is important to acknowledge that C-sections may impose other forms of hardship for mothers that are not captured by my data, such as long-term reproductive consequences (e.g., repeat C-sections) and mental health issues (e.g., postpartum depression). I am also unable to assess the health impacts on infants due to data limitations.

Table 4. Effects on Maternal Health Outcomes

	Length of stay (Poisson)			*Complications (OLS)*			
	(1) Total	(2) Pre-birth	(3) Post-birth	(4) Hemorrhage	(5) Infection	(6) Laceration	(7) Severe
Physician housing return	0.010	-0.004	0.010	-0.139	0.033	0.259	0.103
	(0.005)	(0.029)	(0.004)	(0.224)	(0.173)	(0.203)	(0.099)
Physician FE	✓	✓	✓	✓	✓	✓	✓
Hospital × year-quarter FE	✓	✓	✓	✓	✓	✓	✓
Patient zip × year-quarter FE	✓	✓	✓	✓	✓	✓	✓
Patient covariates	✓	✓	✓	✓	✓	✓	✓
Mean (dep. var.)	2.49	0.35	2.14	2.15	1.29	1.85	0.48
Observations	439,141	439,141	439,141	439,141	439,141	439,141	439,141

Notes: This table reports results from patient-level regressions of maternal health outcomes on physician housing returns. The sample spans 2004 to 2014. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1)–(3) use the days of entire inpatient stay, pre-birth stay, and post-birth stay, respectively, as dependent variables. Columns (4)–(7) use indicators (scaled by 100) for hemorrhage, infection, laceration, and severe complications, respectively. Columns (1)–(3) are estimated using a Poisson model and Columns (4)–(7) are estimated using a linear probability model. All regressions include patient characteristics and fixed effects as in the baseline specification. Standard errors, clustered at the physician level, are reported in parentheses.

VI Potential Mechanisms

The results in this paper have shown that physicians are more likely to perform C-sections in response to negative housing wealth shocks. However, housing shocks can trigger behavioral responses through multiple possible mechanisms. A decline in wealth may increase physicians' marginal utility of income, motivating them to profit from performing more C-sections (i.e., the *wealth effect*). Alternatively, negative wealth shocks may put physicians under liquidity pressure, making them want to recover lost income or avoid future risks (i.e., *financial distress*). Distinguishing between these mechanisms is crucial for interpreting the results and understanding their policy implications. For instance, if the wealth effect drives physician behavior, policies that increase physicians' wealth or income may help reduce C-section rates. If financial distress is the major cause, policies should focus on assisting constrained physicians in managing downside risks.

In Appendix Section E, I introduce a simple conceptual framework to rationalize physicians' treatment choices. This framework incorporates two key motives underlying physicians' decisions—personal earnings from the physician fee (i.e., financial incentives) and medical benefits to the patient (i.e., physician altruism). I discuss different implications of the standard wealth effect and financial distress under this framework. Importantly, the wealth effect should operate symmetrically for both positive and negative shocks, whereas the financial distress channel only kicks in when physicians are exposed to negative shocks and close to liquidity constraints. I perform several empirical tests on these predictions below.

VI.A Asymmetric Responses

I first divide the sample into four sub-periods: a pre-crisis period (2004–2006) when house prices were booming, the onset of the Great Recession (2007–2009) when property values declined most sharply, a stagnation period (2010–2012) when the real estate market remained sluggish, and a post-crisis period (2013–2014) when house prices started to recover slowly. I then repeat the baseline regression for each of these sub-periods separately, with the estimates plotted in Figure 8(a).

From 2004 to 2006, nearly all zip codes experienced an increase in property prices. As illustrated in Figure 2, the median physician's housing return rose from 24% at the beginning of 2004 to 86% by the end of 2006. However, physicians did not respond to these higher housing returns during this period by reducing their C-section rates—the effect of this wealth appreciation is close to zero and statistically insignificant. The estimate becomes statistically significant for 2007–2009 as the financial crisis phased in. This effect remains significant and becomes even larger in the 2010–2012 period as physicians' housing wealth continues to shrink. Finally, the effect winds down when the real estate market rebounds in 2013, a time when most physicians in the data started to experience higher housing returns again.

Taken together, the increase in C-section rates is concentrated in the crisis period (2007–2012) when house values declined. These results are similar to those in the event study analysis and consistent with findings in the household finance literature that agents only respond to negative shocks (e.g., Bernstein et al., 2021; Aslan, 2022).[28] At face value, these results can also be explained by the behavioral theory of loss aversion (Tversky and Kahneman, 1991; Genesove and Mayer, 2001), which posits that individuals weigh losses more than equivalent gains. While I cannot rule out this possibility, evidence in the next subsection points to the role of real financial stakes. Finally, the asymmetric effects may also help explain why C-section rates remained stubbornly high even after the crisis, highlighting the long-lasting effects of physician behavioral responses.

VI.B The Role of Physician Leverage

Physicians with greater debt are more economically vulnerable and thus more likely to experience financial distress. It is more difficult for highly leveraged physicians to manage cash flows, borrow against home equity, or expand their business, among other activities. C-sections may become

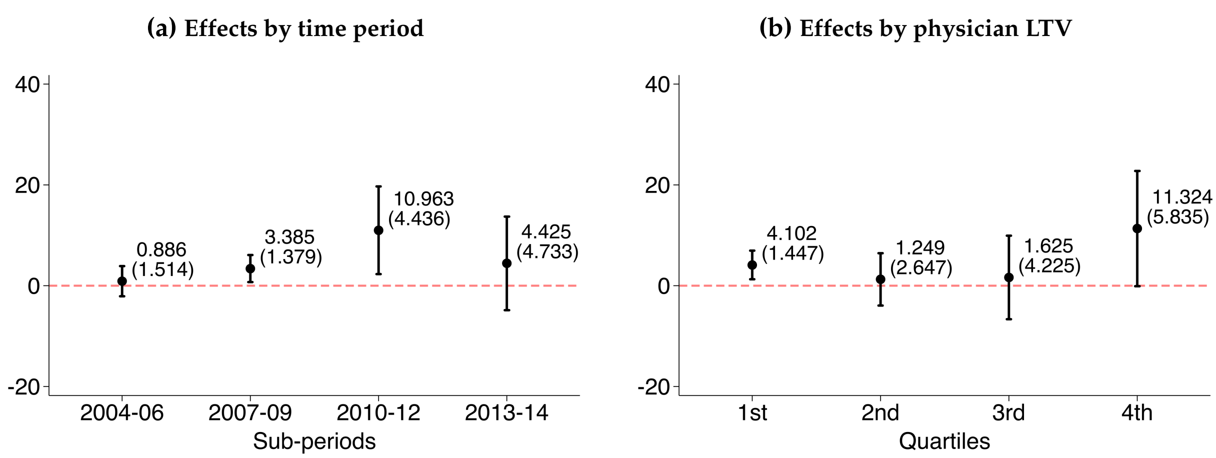
[28] A potential concern is that the house price increase before 2007 and after 2012 might not be a large, unexpected shock to physicians. In fact, the annual increase in cumulative housing return for the median physician before 2007 is 31%, larger than annual decrease during the crisis (23%). It is also worth noting that, to violate the identification assumption, physicians need to anticipate not only the direction of real estate cycles but also zip code-specific house price changes over time.

especially attractive in such circumstances, as they not only offer higher payments but may also serve as a form of defensive medicine for distressed physicians who are less able to bear the risks of malpractice lawsuits, reputational damage, or even job loss.

To measure a physician's leverage, I impute their current Loan-To-Value (LTV) ratio, 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 of a property is estimated as the purchase price multiplied by the cumulative housing return of its zip code. Appendix Figure B6 shows the LTV ratios across physicians. Just prior to the crisis (2006-Q4), the median physician has an LTV ratio of about 31.8%, with the 25th percentile at 16.0% and the 75th percentile at 54.3%. The distribution significantly shifts rightward during the crisis, with the median, 25th percentile, and 75th percentile rising to 43.5%, 21.1%, and 73.5%, respectively, by the end of 2009.

I then divide the sample into four quartiles based on physicians' LTV ratios. Figure 8(b) reports the subsample regression results for these four groups. The coefficient for the highest LTV group is significant and the largest in magnitude among the four groups, supporting the argument that physicians with more limited financial capacity are more responsive to housing wealth shocks. In contrast, estimates for the middle two groups are much smaller and statistically insignificant. The estimate for the lowest LTV group is also significant and close to the full-sample baseline estimate, suggesting that other channels may also play a role, although perhaps not as prominently as the channel of financial distress.

Figure 8. Potential Mechanisms



Notes: Panel (a) plots the subsample regression coefficients for four periods. Panel (b) plots the subsample regression coefficients for four quartiles of physician Loan-To-Value ratios. Point estimates as well as 95% confidence intervals are reported. All regressions include the patient covariates and fixed effects as in the baseline specification. Standard errors are clustered at the physician level.

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 the health of physicians' balance sheets affects clinical decision-making. That said, these findings are suggestive and may not entirely rule out the wealth effect as well as other factors such as psychological stress that may correlate with or even amplify the effects of financial distress (Currie and Tekin, 2015; Engelberg and Parsons, 2016).

VII Conclusion

This paper examines how physicians' financial health influences their treatment decisions and patient health. 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 the use of C-sections when their housing returns decrease. Physicians' responses are concentrated in the delivery mode, rather than through changes in other treatment margins or overall workload. However, there is no evidence that patient health is worse off on average. From a redistribution perspective, insurers likely bear most of the costs by paying higher fees for C-sections, some of which could be passed downstream as greater budget pressure for public payers or higher premiums for private plans.

In the mechanism analysis, I find that the C-section rate increases the most when physicians are more financially constrained, suggesting that financial distress may be a primary mechanism driving the behavioral responses. These findings carry important policy implications. They underscore the potential of policies that integrate financial literacy into medical education, as well as federal programs aimed at improving physicians' financial resilience, such as the Public Service Loan Forgiveness program and the Income-Driven Repayment plan. Notably, federal student loan programs are expected to be scaled back by 2026 under the One Big Beautiful Bill Act, raising concerns about provider vulnerability during future economic downturns. The fact that I find stronger responses among junior physicians and physicians with higher leverage is consistent with the idea that even these high-income professionals can face tight balance-sheet constraints. Policies that help smooth physicians' financial pressures and prevent them from sliding into financial distress may therefore have social value beyond private benefits. That said, the generalizability of these implications will depend on the exact medical specialty, reimbursement system, and economic environment.

More broadly, this paper sheds light on how financial market frictions can spill over to clinical decision-making of healthcare providers. While I focus on housing wealth shocks, real estate is not the only source of financial risk. Other channels, 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 For Publication

A Additional Details on Data and Sample

Inpatient Data and Physician Characteristics. — To construct the analytic sample, I start by extracting all inpatient records associated with labor and delivery from the hospital inpatient discharge data in Florida. Specifically, I keep discharges with a DRG code listed in Table A1 below.

Table A1. DRG Codes for Delivery Type

Delivery type	DRG code
Cesarean delivery	370, 371, 765, 766
Vaginal delivery	372, 373, 374, 375, 767, 768, 774, 775

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. NPIs enable linkage to the National Provider Identifier (NPI) registry of the National Plan and Provider Enumeration System (NPPES). Over 95% 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. 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's guidelines to identify complications *not* present at the time of admission. Appendix Table A2 summarizes the codes used for maternal morbidity.

Table A2. ICD Codes for Maternal Morbidity

Maternal morbidity	Diagnosis code starting with:	Procedure code starting with:
Hemorrhage	666 285.1	
Infection	670 672 659.2 659.3	
Laceration	664.2 664.3	
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

Physicians' 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$\times$house$\times$date level. To achieve this, I first collapse the data to the physician$\times$house$\times$date$\times$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$\times$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$\times$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.

Lastly, I merge house transaction records with mortgage information. This final step does not result in any loss of observations. Houses without matched mortgage records are assumed to have been purchased in cash.

House Prices. — The matched housing data from CoreLogic is then used to calculate physicians' cumulative housing returns. I use the Zillow House Value Index (ZHVI) to measure the value of a house in a given zip code at a given calendar quarter. The ZHVI is available starting from the year 2000. 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. 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: $HPI_t^{\text{ZHVI}} = \gamma \cdot HPI_t^{\text{FHFA}}, \forall t < 2000$.

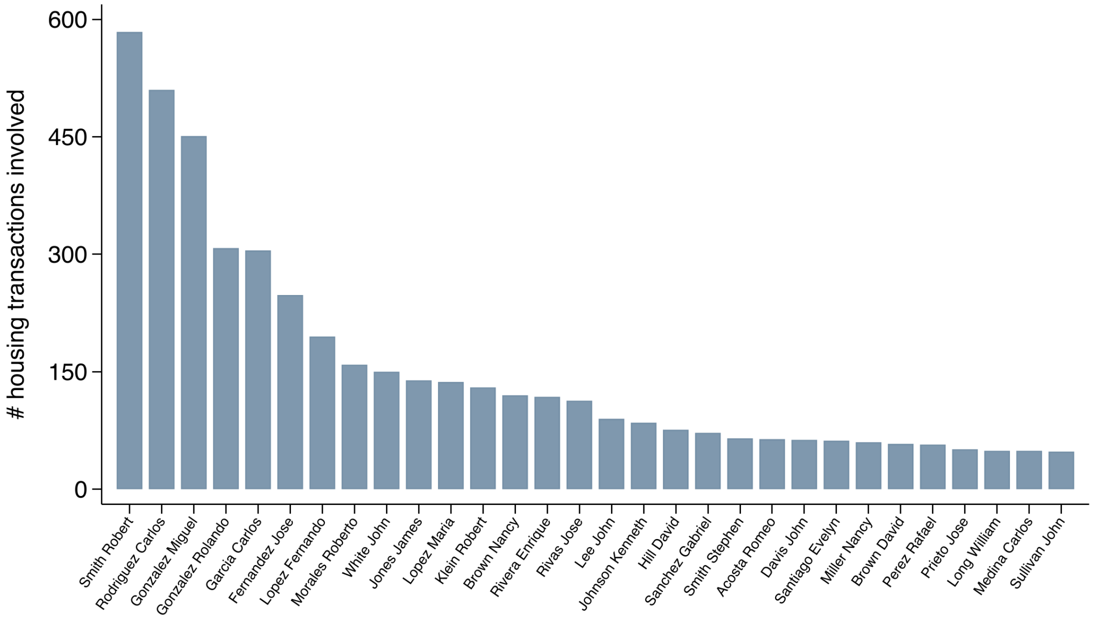
The Analytic Sample. — From the matched sample of inpatient records and CoreLogic data, I apply both patient-side and physician-side filters to construct the analytic sample. Table A3 below summarizes these sample construction steps and the attrition in the numbers of cases and physicians at each step (percentages in parentheses are relative to the top row).

Table A3. Sample Construction

Steps	# Births	# Physicians
All childbirths in the matched sample	2,194,202	17,140
Panel A: Filters on patients		
(1): Drop missing key variables	2,133,623 (97.2%)	17,139 (100.0%)
(2): Keep Florida residents	2,114,633 (96.4%)	16,970 (99.0%)
(3): Keep maternal age 18–50	2,006,532 (91.4%)	10,519 (61.4%)
(4): Keep length of stay 0–7 days	1,977,012 (90.1%)	9,617 (56.1%)
(5): Keep low-risk patients (singleton, no prior C-section)	1,595,712 (72.7%)	9,267 (54.1%)
Panel B: Filters on physicians		
(6): Exclude 0% or 100% C-section physicians	1,560,367 (71.1%)	5,284 (30.8%)
(7): Keep attending physician = operating physician	1,147,403 (52.3%)	2,429 (14.2%)
(8): Keep continuously practicing physicians	906,129 (41.3%)	920 (5.4%)
(9): Drop inactive physicians	906,094 (41.3%)	892 (5.2%)
(10): Drop physicians with dubious matches from CoreLogic	771,302 (35.2%)	758 (4.4%)

Step (10) in Table A3 is devoted to reducing matching errors by excluding physicians matched with too many properties (> 3), and those with common names. It is difficult to come up with a universally accepted definition of "common names." I therefore adopt a more parsimonious data-driven approach. More specifically, I define a common name as one associated with more than 10 different housing transactions from the matched CoreLogic sample. Figure A1 reports the top 30 names that are associated with the most transactions as well as the number of transactions associated with each name. The list includes both common names such as "Smith Robert" and also Hispanic names such as "Rodriguez Carlos", which is probably not surprising as Florida has a significant Hispanic population.

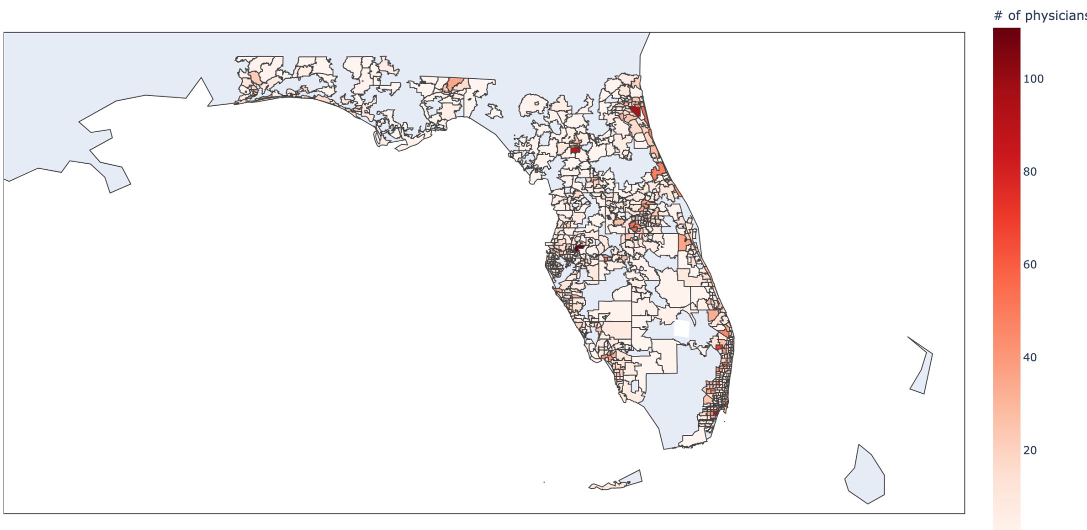
Figure A1. Top-30 Common Names Excluded from the CoreLogic Match



B Additional Details on Key Variables

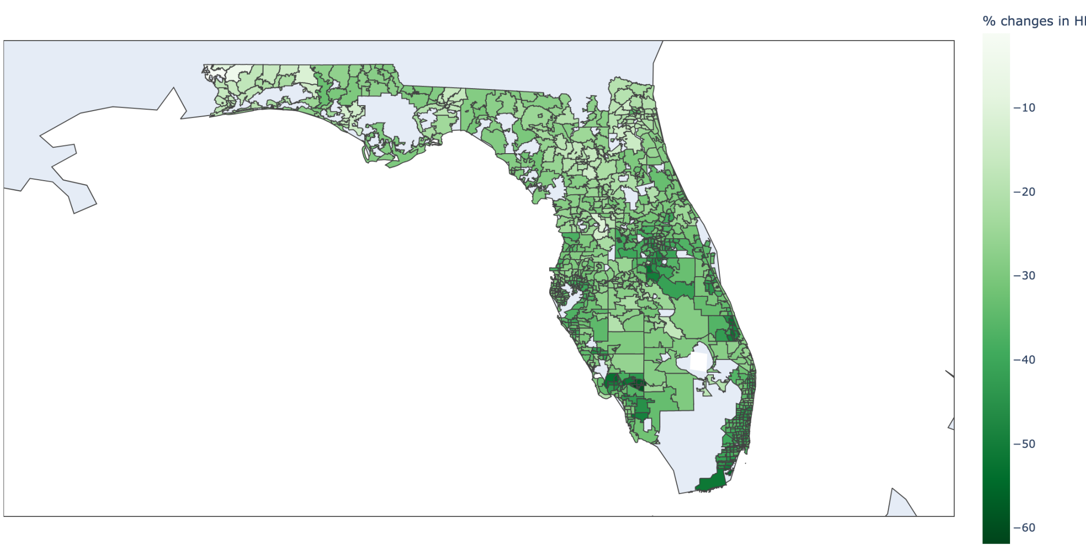
Physician Cumulative Housing Returns. — The cumulative housing return combines two sources of variation: (1) the zip code(s) where a physician's house is located, and (2) the time when the physician purchased the house(s). Figure B1 maps the number of physicians residing in each zip code. Figure B2 shows the percentage change in $ZHVI$ during the crisis across zip codes.

Figure B1. Number of Physicians by Zip Code



Notes: This figure shows the number of physicians residing in each Florida zip code. Zip codes with missing data of Zillow House Value Index (ZHVI) are excluded.

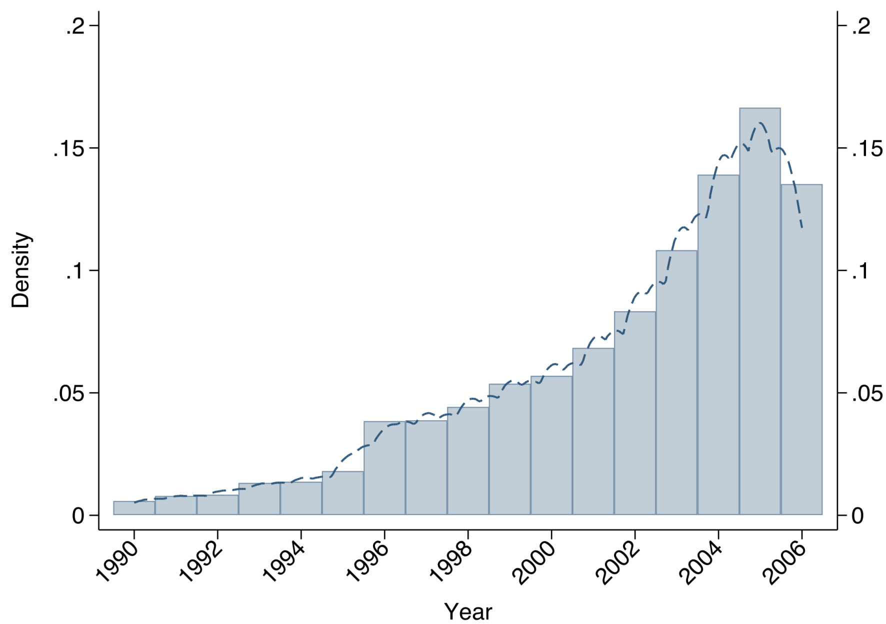
Figure B2. Changes in housing values by Zip Code



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

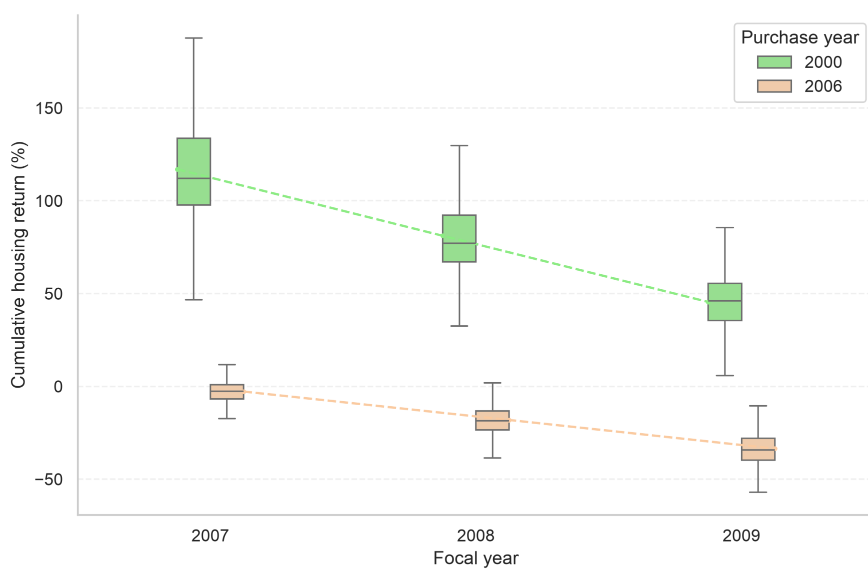
Figure B3 displays the distribution of physicians' home-purchasing time in the sample. Figure B4 shows that how physicians' cumulative returns would have been different had physicians purchased their homes in an earlier year rather than later.

Figure B3. Fractions of Physicians by Purchase Year



Notes: This histogram shows the fraction of physicians purchasing their homes in various years. Purchases before 1990 or after 2006 are excluded. The dashed line represents the kernel density.

Figure B4. Cumulative Returns by Purchase Year



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

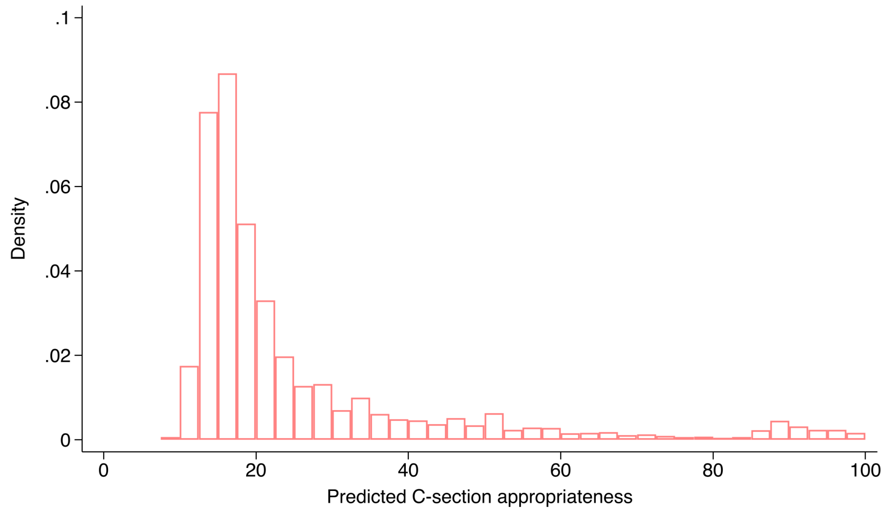
Patient C-section Appropriateness. — Each patient's "appropriateness" of receiving a C-section (or "C-section risk") is estimated by a Logit regression model with a binary indicator for C-section as the outcome and all patient demographics and risk factors as predictors. To avoid potential selection, all patients in both the homeowner and non-homeowner samples are included in the prediction. Table B1 reports the results from the Logit regression. Figure B5 shows the distribution of the predicted C-section appropriateness.

Table B1. **Nonlinear Probability Model (Logit Model)**

	C-section Rate	
	Coef.	S.E.
Non-hispanic white	-0.181***	(0.033)
Non-hispanic Black	-0.109**	(0.036)
Hispanic	0.184***	(0.041)
Medicaid	0.128***	(0.034)
Commercial	0.301***	(0.032)
Weekend delivery	-0.196***	(0.019)
35 years of age or older	0.252***	(0.015)
Malposition or malpresentation of fetus	4.225***	(0.063)
Preterm	-0.035	(0.024)
Asthma	0.051	(0.030)
Polyhydramnios or oligohydramnios	0.691***	(0.036)
Physical abnormalities	0.866***	(0.031)
Blood disorders or issues	1.474***	(0.041)
Uterine size issues	0.320***	(0.037)
Infant size issues	1.669***	(0.048)
Obesity	0.686***	(0.044)
Anemia	0.397***	(0.034)
Malnutrition or insufficient prenatal care	-0.388***	(0.040)
Diabetes	0.414***	(0.022)
Smoking, and alcohol or drug dependence	-0.105**	(0.035)
Infectious and parasitic conditions	0.728***	(0.040)
Heart diseases	0.213***	(0.042)
Fetal abnormality	0.453***	(0.056)
Antepartum fetal distress	1.651***	(0.114)
Hypertension	0.861***	(0.022)
Isoimmunization	-0.167***	(0.035)
Premature rupture of the amniotic sac	0.214***	(0.035)
Other complications of pregnancy	0.269***	(0.044)
Observations	439,141	

Notes: This table reports estimates from the Logit regression using patient-level data from 2004 to 2014. The outcome variable is a binary indicator for C-section (scaled by 100). Regressors include patient covariates such as demographics, insurance type, weekend delivery, and clinical risk factors. Column (1) reports the estimated coefficient and Column (2) reports the standard errors clustered at the physician level.

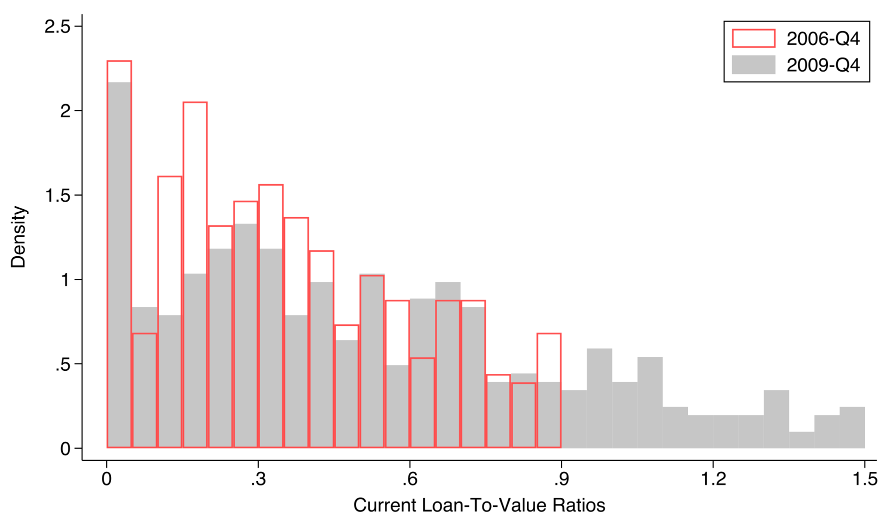
Figure B5. Distribution of Predicted C-section Appropriateness



Notes: This histogram shows the distribution of predicted C-section appropriateness for patients in the analytic sample.

Physician Loan-To-Value Ratio. — A property's current Loan-To-Value (LTV) ratio is 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 of a property is estimated as the purchase price multiplied by the cumulative housing return of its zip code. A physician's LTV is then the weighted average of the LTV ratios of all properties they own.

Figure B6. Distribution of Physician Loan-To-Value Ratios

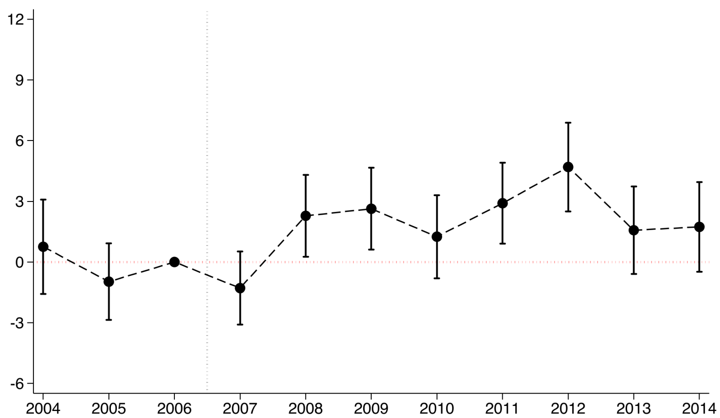


Notes: This histogram shows the distribution of physicians' Loan-To-Value ratios at the time of 2006-Q4 and 2009-Q4, respectively.

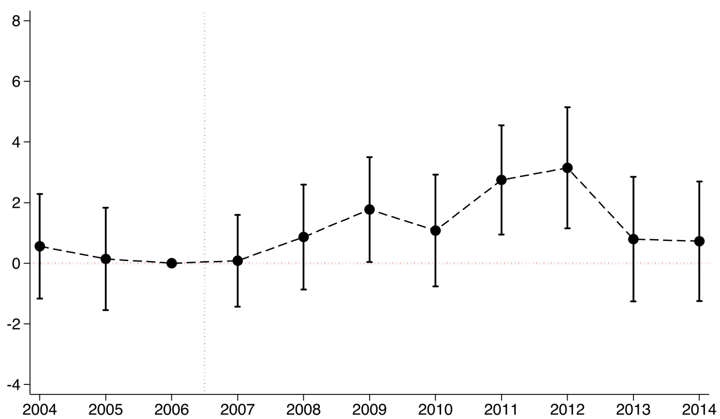
C Additional Details on the Event Study

Figure C1. Additional Event Study Coefficient Plots

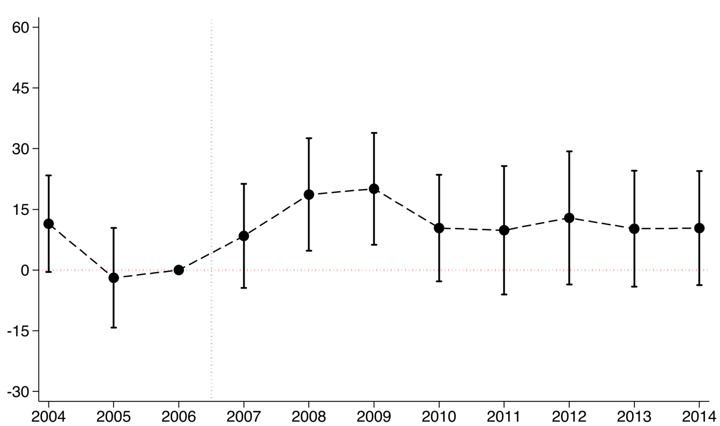
(a) Treatment defined over longer window



(b) Binary treatment



(c) Zip code-level treatment

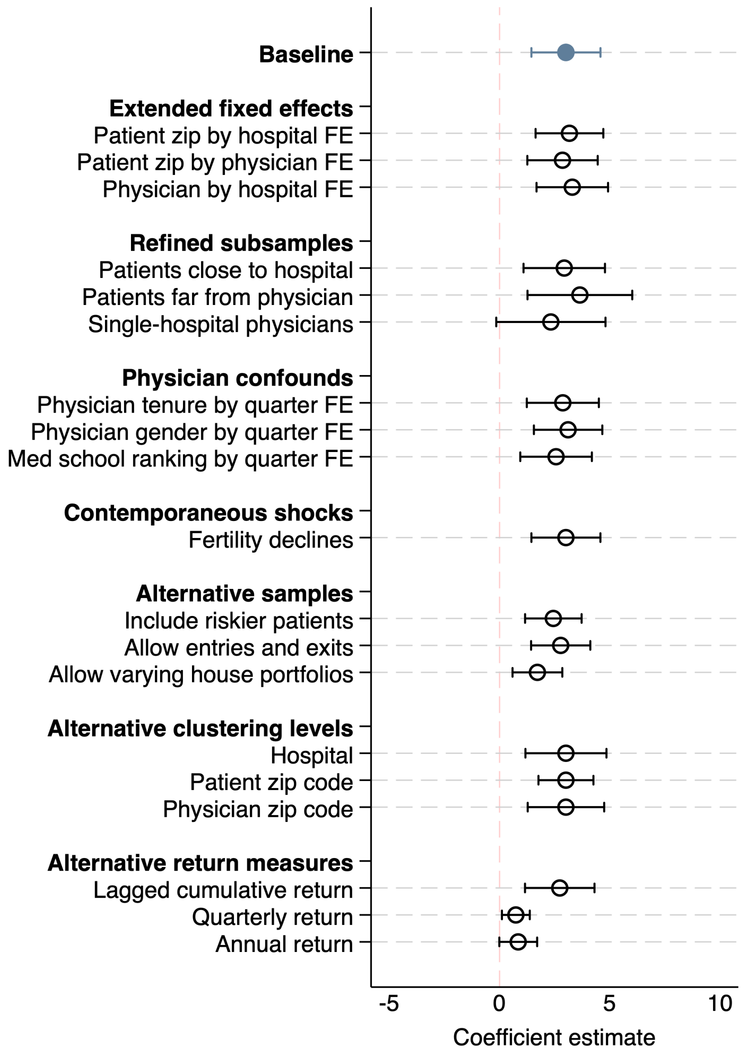


Notes: These figures are additional event-study coefficient plots. All regressions follow the event study specification (Equation (3)). Panel (a) uses the physician-level shock defined over 2007–2012. Panel (b) uses an above-median treated dummy based on the physician-level shock defined over 2007–2009. Panel (c) uses the zip code-level housing shock defined over 2007–2009.

D Additional Results

Additional Tests under the TWFE Specification. — Results of several additional tests are summarized in Figure D1. Details of these tests are discussed in Section IV.C.

Figure D1. Additional Tests



Notes: This figure collects coefficient estimates from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model. The blue top row reports the estimate from the baseline specification. The blue top row reports the estimate from the baseline specification and black rows report subgroup estimates with 95% confidence intervals.

Effects on Non-Hispanic Black Patients. — Table D1 explores why the treatment effect is larger for non-Hispanic Black patients. Intuitively, this could be explained by: (1) physicians who treat Black patients are more affected by the housing shocks, (2) Black patients are riskier and therefore more likely to receive a C-section, or (3) physicians' behavioral responses (e.g., inaccurate beliefs, discretionary treatments, etc) for Black patients specifically. Column (1) regresses the Black patient indicator on physician housing return as in the patient-level balance test. Column (2) runs a physician×year-quarter panel regression with a ratio of Black patients ($\frac{\#\text{Black patients}}{\#\text{Total patients}}$) as the outcome and physician housing return as the independent variable. Results show that more affected physicians do not disproportionately treat more Black patients over time, ruling out the first explanation. Column (3) regresses the predicted C-section risk on the Black patient indicator and finds that risk scores for Black patients are actually lower than those for non-Black patients, ruling out the second explanation. Although hard to test directly, the third explanation of behavioral responses seems more likely to underlie the larger effect for Black patients.

Table D1. Effects on Non-Hispanic Black Patients

Dep. Var: Indep. Var:	Black patient indicator Physician housing return (1)	Black patient ratio Physician housing return (2)	Patient risk Black patient indicator (3)
2004–2006	-0.013	0.005	-1.227***
	(0.013)	(0.016)	(0.169)
# obs	128,623	4,562	128,623
2007–2009	0.015	0.007	-0.841***
	(0.012)	(0.011)	(0.171)
# obs	129,428	4,889	129,428
2010–2012	0.052	0.028	-1.246***
	(0.050)	(0.046)	(0.185)
# obs	112,017	4,884	112,017
2013–2014	-0.004	-0.052	-0.958***
	(0.038)	(0.043)	(0.215)
# obs	69,073	3,240	69,073
Full sample	0.007	0.005	-1.105***
	(0.008)	(0.010)	(0.105)
# obs	439,141	17,575	439,141
Physician FE	✓	✓	✓
Hospital × year-quarter FE	✓		✓
Patient zip code × year-quarter FE	✓		✓
Year-quarter FE		✓	
Sample	patient level	physician×quarter level	patient level

Notes: Columns (1) and (3) are patient-level linear regressions with physician, hospital-by-year-quarter, and patient zip code-by-year-quarter fixed effects. Column (2) is a physician×year-quarter panel regression with physician and year-quarter fixed effects. Standard errors are clustered at the physician level.

Marginal C-sections. — In the spirit of Gruber et al. (1999), I estimate the following specification at the physician (j)×year-quarter (t) level.

$$\text{Avg Patient Risk of C-section Births}_{j,t} = \alpha \cdot log(\text{C-section Rate})_{j,t} + \theta_j + \lambda_t + \epsilon_{j,t} \qquad \text{(D-1)}$$

The outcome variable is the average C-section risk among the actual C-section births for a specific physician in a specific quarter. The C-section risk is predicted by a Logit model, as described in the paper. On the right-hand side is the physician×quarter-level (logged) C-section rate. The coefficient $\hat{\alpha}$ captures the difference in patient risk between the marginal C-section birth and the average C-section birth. For example, if $\hat{\alpha}$ is positive, it would suggest that the marginal C-section birth is riskier and thus more appropriate for a C-section. In contrast, if $\hat{\alpha}$ is negative, it would suggest that the marginal C-section birth probably should not have been delivered through C-section absent the shock.

Column (1) of Table D2 considers a simple OLS regression of Equation (D-1). The C-section rate coefficient is negative but statistically insignificant. Columns (2)–(4) consider using the financial crisis as an instrument for the C-section rate. Specifically, I construct the IV as $Shock_j \times Post_t$ where $Shock_j$ is exactly the same physician-level exposure to the housing shock as in the event study, and $Post_t$ is an indicator for years after 2007. Column (2) reports the corresponding reduced-form estimate for this IV: the coefficient on $Shock_j \times Post_t$ is insignificant, indicating that the average patient risk among C-section births does not change substantially after the shock. Columns (3) and (4) follow the 2SLS procedure formally. The first-stage estimate in Column (3) shows that negative housing shocks significantly predict higher C-section rates, with an F-statistic of 9.52. The second-stage estimate in Column (4) is close to zero and statistically insignificant. Taken together, these results suggest that the risk profile of marginal C-section births is not significantly different from that of average C-section births.

Table D2. Marginal C-sections

	(1) OLS	(2) Reduced-Form	(3) IV: First-Stage	(4) IV: Second-Stage
Log(C-section rate)	-0.221			0.596
	(0.259)			(8.096)
Shock × Post		0.048	0.081	
		(0.654)	(0.026)	
Physician FE	✓	✓	✓	✓
Year-quarter FE	✓	✓	✓	✓
# Observations	16,670	16,670	16,670	16,670

Notes: This table reports results for the marginal C-section analysis following Equation (D-1). The outcome variable is predicted C-section risk (scaled by 100) aggregated to physician×year-quarter level. Column (1) reports the OLS estimate. Columns (2)–(4) use $Shock_j \times Post_t$ as an instrument for the C-section rate. Column (2) reports the reduced-form estimate; Column (3) reports the first-stage estimate; Column (4) reports the second-stage estimate. All specifications include physician and year-quarter fixed effects. Standard errors are clustered at the physician level.

Effects on Other Outcomes by Delivery Mode. — Effects of physician housing returns on other treatment margins and maternal health are estimated separately for C-section and vaginal births.

Table D3. Effects on Other Treatment Margins (by Delivery Mode)

	(1) Induction	(2) Vacuum/Forceps	(3) Hosp. charges
Panel A: Cesarean births			
Physician housing return	-2.154	0.352	-0.016
	(0.995)	(0.456)	(0.009)
Mean (dep. var.)	15.23	2.49	9.81
Observations	110,401	110,401	110,401
Panel B: Vaginal births			
Physician housing return	-0.293	0.802	-0.006
	(0.863)	(0.577)	(0.006)
Mean (dep. var.)	21.58	5.22	9.18
Observations	328,740	328,740	328,740
Physician FE	✓	✓	✓
Hospital × year-quarter FE	✓	✓	✓
Patient zip × year-quarter FE	✓	✓	✓
Patient covariates	✓	✓	✓

Note: Panels A and B report results on other treatment margins for C-section and vaginal births, respectively. Columns (1)–(2) use indicators, scaled by 100, for labor induction and vacuum/forceps as outcomes; Column (3) uses logged hospital charges. All specifications include patient covariates and fixed effects as in the baseline specification. Standard errors are clustered at the physician level.

Table D4. Effects on Patient Health (by Delivery Mode)

	(1) Hemorrhage	(2) Infection	(3) Laceration	(4) Severe
Panel A: Cesarean births				
Physician housing return	-0.085	-0.017	-0.008	0.009
	(0.392)	(0.364)	(0.027)	(0.300)
Mean (dep. var.)	2.52	2.36	0.01	1.18
Observations	110,401	110,401	110,401	110,401
Panel B: Vaginal births				
Physician housing return	-0.210	-0.057	0.417	0.123
	(0.266)	(0.172)	(0.281)	(0.079)
Mean (dep. var.)	2.00	0.94	2.47	0.24
Observations	328,740	328,740	328,740	328,740
Physician FE	✓	✓	✓	✓
Hospital × year-quarter FE	✓	✓	✓	✓
Patient zip × year-quarter FE	✓	✓	✓	✓
Patient covariates	✓	✓	✓	✓

Note: Panels A and B report results on maternal complications for C-section and vaginal births, respectively. Columns (1)–(4) use indicators, scaled by 100, for hemorrhage, infection, laceration, and severe complications. All specifications include the baseline patient covariates and fixed effects. Standard errors are clustered at the physician level.

E Conceptual Framework

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

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:

$$\max_{k \in \{v,c\}} : U_{i,j,k} = \underbrace{f_j(\omega_k)}_{\substack{\text{personal earnings} \\ \text{to physician}}} + \underbrace{b_k(X_i)}_{\substack{\text{medical benefits} \\ \text{to patient}}} \tag{E-2}$$

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

The second component in Equation (E-2), $b_k(X_i)$, represents the medical benefit to patient i with characteristics X_i from receiving treatment k. A larger $b_k(X_i)$ indicates that, all else equal, treatment k is more appropriate for the patient, and thus choosing a treatment other than k imposes greater disutility on the physician. This disutility arises from physicians' "internal conscience" and reflects physician altruism.

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

$$b_v(X_i) - b_c(X_i) \leq f_j(\omega_c) - f_j(\omega_v) \tag{E-3}$$

The left-hand side of Equation (E-3), $b_v(X_i) - b_c(X_i)$, 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. Let $\mathbf{B}(\cdot)$ denote the distribution function of $b_v(X_i) - b_c(X_i)$ across patients. The probability of patient i receiving a C-section can be written as:

$$p_i = \mathbf{B}\big(f_j(\omega_c) - f_j(\omega_v)\big) \tag{E-4}$$

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

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

The first possible mechanism is the standard wealth effect (or income 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's housing wealth decreases, their marginal utility of income increases, strengthening the incentive to earn additional income from C-sections. A distinctive feature of this mechanism is that it operates in both directions. In other words, a positive shock that increases physician wealth would lower their marginal utility of income, persuading them to perform fewer C-sections.

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

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