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

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June 13, 2025

**Abstract**

This paper examines how physicians' financial health influences their treatment decisions and patient outcomes in the context of childbirth. I leverage a novel data that links physicians' real estate portfolios to patient hospitalization records, and exploit within-physician variation in housing returns for identification. A one-standard-deviation decline in physician housing returns increases C-section rates by 1.6 percentage points, or 4%. However, there is no clear evidence that maternal health outcomes are substantially affected. Finally, I show that physicians' responses are primarily driven by financial distress, with C-sections used as a strategy of defensive medicine to avoid potential malpractice costs.

**JEL Codes**: D14, G51, I11, I14, J44
**Keywords**: financial distress, physician behavior, patient health

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# I Introduction

Spending on physician services is substantial and growing in developed countries (Martin et al., 2025). In the U.S., National Health Expenditure (NHE) on physician and clinical services increased by 7.4 percent and reached 978 billion dollars in 2023, accounting for overall 3 percent of domestic GDP. Prior studies have shown that physician care provision is responsive to financial incentives from volume-based payment schemes (Clemens and Gottlieb, 2014; Batty and Ippolito, 2017; Brekke et al., 2017), and that physicians are incentivized to adopt more profitable treatment options, even if it is not necessarily for patients' best interest (Gruber et al., 1999; Coey, 2015; Alexander, 2017). However, little is known about how physicians' own financial health affects their treatment decisions.

Physicians' financial health is susceptible to shocks from financial markets. On the one hand, physicians are among the top earners in the country (Gottlieb et al., 2025), with a considerable portion of their wealth tied to assets such as stocks and real estate properties. Volatile returns on these assets can expose physicians to unpredictable wealth losses and even create financial distress.[1] On the other hand, physicians are often burdened with substantial personal debt, such as student loans and mortgages, particularly early in their careers.[2] The health of their balance sheets can be sensitive to shocks such as interest rate changes and policies such as student loan forgiveness programs.

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

Directly estimating the causal effect on physician behavior presents an important empirical challenge — treatment choices could potentially be confounded by patient demand. For instance, physicians in poorer financial health may face different incentives when treating patients with var-

[1] According to Medscape's Physician Wealth and Debt Report (2021), about one-third of physicians experienced significant financial losses in 2020, during the onset of the COVID-19 pandemic and subsequent economic turmoil. Among specialists who admitted to making investment mistakes, 44% reported losses from investments in stocks or real estate. See https://www.medscape.com/slideshow/2021-compensation-wealth-debt-6013910.

[2] The median education debt among medical school graduates reached $200,000 in 2021 (Association of American Medical Colleges, 2020).

ious risk profiles. Moreover, financial shocks to physicians may correlate with those experienced by their patients, potentially influencing healthcare utilization (Acemoglu et al., 2013; Tran et al., 2023) or even underlying health (McInerney et al., 2013; Fichera and Gathergood, 2016; Schwandt, 2018). To address this concern explicitly, I link real estate data to hospital discharge records in Florida, which enables me to condition my identification on a detailed list of demand-side covariates at the patient level.

I also focus on a specific clinical setting, labor and delivery, or childbirth. This inpatient setting has several advantages for my purpose.[3] First, the major treatment margin is well-defined in this setting — vaginal delivery versus cesarean section (C-section). Physicians in this context (i.e., obstetricians and gynecologists, or OB-GYNs) have relatively large discretion in recommending treatment choices (Gruber and Owings, 1996; Johnson and Rehavi, 2016). Second, it has been widely documented that C-sections pay more generously to physicians than vaginal deliveries on average (Corry et al., 2013). C-sections are also generally perceived as a strategy of defensive medicine which reduces the risk of malpractice (Currie and MacLeod, 2008). I therefore hypothesize that physicians in worse financial conditions are more tempted to perform C-sections, all else equal.

For empirical tests, I first construct a physician-level, time-varying measure of cumulative housing returns, defined as the change in house value relative to the purchase price. Existing studies in household finance have used this measure to proxy for households' wealth shocks and financial distress (Gerardi et al., 2018; Dimmock et al., 2021). I then assume that physicians' house-purchasing decisions are made before the financial crisis which they could not have foreseen, and so that their housing returns are unlikely to correlate with potential patient treatments ex post. With this assumption, I estimate a patient-level regression model using within-physician variation in housing returns, which is mainly driven by more aggregate house price movement over the business cycle, after conditional on pre-determined housing portfolios.

To separate responses to housing wealth shocks from time-invariant confounds at the physician level, I include physician fixed effects in the baseline specification to control for factors such as physician preferences and skills. To account for contemporaneous financial shocks and changes in incentives at the hospital level, I also control for hospital×time fixed effects. I find that a one-standard-deviation decrease in physicians' housing returns leads to an increase of 1.6 percentage points in the probability of C-section, which represents a 4% increase relative to the average. This effect is even pronounced (2 percentage points, or 9%) among a subset of patients who are flagged as clinically low-risk and considered natural candidates for vaginal delivery.

To rule out the demand-side channel, I first show through a balance test that physician housing returns are conditionally independent of observed patient demographics and risk factors. In other words, results are unlikely to be driven by physicians cherry-picking certain patients or patients self-selecting into certain physicians. Next, I confirm that results are robust to concurrent wealth

[3]This is also a high-stakes setting. There are approximately 4 million newborns in the U.S. each year. Childbirth-related hospitalizations account for 11% of all hospital stays and 4% of all inpatient hospital costs (Podulka et al., 2011).

shocks to patients by additionally including patient zip code$\times$time fixed effects in the regression. Finally, I find that the increase in C-section rates is concentrated in unscheduled cases as opposed to scheduled ones, which would not have been the case if medical necessity or maternal request were the primary reason for higher C-section rates.

The effect of financial health on treatment choices varies across physicians. Specifically, physicians who performed fewer excessive C-sections ex ante, who practice in less competitive markets, and female physicians are more responsive to lower housing returns. This effect could also be unequal for different patients. I find that patients whose medical benefits from C-sections and vaginal deliveries are similar (i.e., "marginal" patients) are more likely to be affected since it is less costly for physicians to recommend them inappropriate treatments. I also estimate that non-Hispanic Black patients are more than twice as likely to receive C-sections when their physicians experience a negative financial shock, suggesting that racial disparities could even widen in economic downturns.

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

As the last part of results, I study the potential channels through which financial shocks alter physicians' treatment choices. I start by proposing a discrete-choice framework of treatment choices in childbirth, which incorporates three important motives behind physicians' decisions: financial incentives, malpractice concerns, and patient welfare. This framework outlines two distinct mechanisms through which patients' medical benefits could give way to physicians' personal interest. The first mechanism operates through the typical *wealth effect* — physicians' marginal utility of income can increase as their housing wealth decreases, motivating them to adopt the more lucrative treatment. The second mechanism stems from *financial distress* — declining house equity limits physicians' financial capabilities, making them want to avoid malpractice liability when they are financially vulnerable.

Evidence supports physician financial distress as the primary mechanism underlying the higher C-section rate. First, I find null results in years leading up to the crisis when physicians' house values were rising, which is consistent with the idea that financial distress is only triggered by negative wealth shocks. Second, results are statistically and economically more significant for physicians who are more likely to be financially distressed, as measured by high Loan-To-Value (LTV) ratios. Third, physicians with lower housing returns perform more assisted procedures, an attempt to defend themselves from accusations of "rushing to a C-section" or "doing nothing." Finally, physicians do not appear to see more patients in response to negative wealth shocks, which would be unlikely if the wealth effect had dominated.

By bridging the literature on household finance and healthcare, this paper contributes to a small but growing body of research on how provider financial health affect medical treatment and patient outcomes. Previous studies have mostly focused on strategies of institutional providers in the face of financial shocks. For example, Aghamolla et al. (2024) find that hospitals exposed to credit rationing increase resource utilization but at a cost of care quality. Adelino et al. (2022) find that hospitals with greater investment losses from the financial crisis increase the use of more intensive treatments. Dranove et al. (2017) find that hospitals that experienced asset depreciation in the stock market did not increase prices but cut unprofitable service offerings. Gao et al. (2024) find that non-profit hospitals can absorb financial pressures and maintain care quality better than for-profit counterparts.[4] To the best of my knowledge, this paper is the first to measure wealth shocks at the individual physician level. In addition, my regression design controls for hospital×time fixed effects, helping to isolate physicians' responses from contemporaneous responses at the facility level.

More broadly, this paper adds to the literature on real effects of financial distress. Previous studies have shown that housing wealth shocks influence a spectrum of household decisions, including consumption (Mian et al., 2013), labor supply (Bernstein, 2021), fertility (Lovenheim and Mumford, 2013), education (Lovenheim, 2011), political participation (McCartney, 2021), as well as worker performance in a range of 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, and central to today's healthcare systems. I show that financial distress can potentially distort physicians' professional decisions, producing profound externalities on public health. The inpatient-level healthcare data also allows me to control for rich characteristics about the downstream consumers, which is often missing in household finance research.

The fact that my analysis is centered around the Great Recession also makes this paper related to the literature on how recessions affect health (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 except for Stevens et al. (2015) which suggests cyclical fluctuations in the quality of nursing home care. My research enriches the understanding of this supply-side channel by providing direct evidence on how shocks originated from the real estate market could have spillover effects on public health by changing physician behavior.

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

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

The remainder of this paper proceeds as follows. Section II introduces the clinical setting and Section III introduces the data and empirical design. I present the main results in Section IV and discuss the mechanisms in V. Finally, Section VI concludes the paper.

## II Setting

Childbirth is the most common cause of hospitalization in the U.S. — there are about 4 million childbirth-related hospital stays each year, accounting for more than 10% of all inpatient stays (Podulka et al., 2011). The primary treatment choice in childbirth is between vaginal delivery and cesarean section (C-section). Among all newborns in the U.S. nowadays, approximately one-third are delivered via C-section. today (Osterman et al., 2023). This C-section rate is double than the level in 1980, not only higher than those in most developed countries but also 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). In Florida, for example, the C-section rate has remained above 40% since 2007 and was among the highest in the U.S. by 2020 (see Figure 1).[5]

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

[5] Estimated by the author using Florida's hospital discharge data. A similar pattern was found by the Health Care Cost Institute using data from patients covered by ESI or Medicaid. See `https://healthcostinstitute.org/all-hcci-reports/one-third-of-births-occurred-by-c-section-in-esi-and-medicaid-in-2020-1` for more details.

diagnosing conditions that justify a C-section.

Cesarean procedures can be life-saving for certain patients, especially for those with severe medical conditions. They can also save infants from the uncertainties of prolonged and difficult labor. On the other hand, although rarely leading to maternal mortality, C-sections increase the risk of maternal morbidity, including complications such as infection, hemorrhage, and blood clots during and after delivery. Due to their invasive nature, C-sections often require a longer hospital stay (2–4 days compared to 1–2 days for vaginal deliveries) and recovery time after discharge (6–8 weeks compared to 2–6 weeks for vaginal deliveries). C-section patients are more likely to be re-hospitalized and to require additional C-sections in future pregnancies. Finally, C-sections may also negatively affect infants, causing injuries during delivery and increasing the risk of future respiratory and immune system issues.[6] The potential overuse of C-sections, especially for low-risk patients, has therefore raised concerns. Public health agencies and policymakers have advocated for reducing unnecessary C-sections. For instance, the Department of Health and Human Services (HHS) has set a target C-section rate for low-risk women of 23.6% by 2030 under the Healthy People Initiative, representing a significant reduction from the most recent level.

Financial incentives are cited as a key driver behind the rising adoption of C-sections (Gruber and Owings, 1996; Gruber et al., 1999; Johnson and Rehavi, 2016; Alexander, 2017). The average physician fee for C-sections was about one-third higher than that for vaginal deliveries in the late 1980s and about 10%–20% higher in more recent years for both Medicaid and commercial insurers (Corry et al., 2013).[7] While C-sections are more financially rewarding, they are not necessarily more labor-intensive. Vaginal deliveries often involve greater uncertainty in waiting time and require continuous monitoring during labor, which may last several hours. In contrast, C-sections typically take only 45–60 minutes, reducing opportunity costs and offering "convenience" to physicians (Keeler and Brodie, 1993).

A C-section, though invasive, is often perceived as a legally safer option—a form of defensive medicine intended to demonstrate that "everything possible was done" to prevent potential harm. Failure to perform a timely C-section is a common allegation in malpractice suits and can result in multimillion-dollar settlements. As Dr. Ronald J. Wapner, Director of the Division of Maternal and Fetal Medicine at Columbia, explains: "If you have a bad outcome and haven't performed a C-section, you are at significant risk legally. In an environment driven by fear of litigation, you're less willing to wait. That absolutely has an impact" (Bakalar, 2005). Physicians are also able to hedge against these risks through malpractice insurance, and perhaps for this reason, previous studies have not found strong evidence of a relationship between liability risk and C-section rates (Dubay et al., 1999; Currie and MacLeod, 2008; Dranove and Watanabe, 2010; Bertoli and Grembi,

[6] Card et al. (2023) summarizes the clinical literature on maternal and infant health effects of C-sections.

[7] Using data from MarketScan during 2004–2010, they report that commercial insurers paid $3,350 and $2,887 for cesarean and vaginal deliveries as professional service fees, respectively (Medicaid paid $1,654 and $1,445, respectively). Physicians may also receive higher reimbursements from cesarean-related services (e.g., anesthesiology, laboratory, radiology, and pharmacy fees) and, in some cases, additional dividends from their ownership in the facilities. There are also financial incentives at the hospital level. For example, commercial insurers (Medicaid) paid $9,933 and $6,738 ($4,358 and $3,102) for cesarean and vaginal deliveries as facility fees, respectively.

2019).

Taken together, the clinical setting of childbirth is particularly useful as physician discretion likely plays a significant role in deciding which medical treatment a patient should receive. C-sections appear to be more economically advantageous for physicians than vaginal deliveries (i.e., higher financial returns and lower malpractice risks). Throughout the empirical analysis, I therefore assume that physicians in weaker financial positions are more motivated to adopt C-sections. I further discuss the potential mechanisms behind this assumption and findings in Section V.

# III Data and Empirical Design

## III.A Data

To measure physician behavior and patient outcomes, I use de-identified hospital inpatient discharge data from the Agency for Health Care Administration (AHCA) of Florida. This data includes patients insured by all payers and discharged by all hospitals in the state. For each inpatient discharge, it provides basic patient demographics, including age, race and ethnicity, gender, insurer, and etc. I further identify patients' comorbidities using ICD-9 diagnosis codes and medical service provision through ICD-9 procedure codes. This data also allows me to observe a series of patient outcomes, such as length of stay, discharge status, and hospital charges. I begin by extracting hospital inpatient records related to childbirth, and focus on patients aged 18 to 50, with a length of stay no longer than 7 days, a residence address in Florida, and no missing demographic information. For example, from 2007-Q1 to 2009-Q4, there are 560,855 childbirths identified in the data, among which about 40% are delivered by C-sections.

An important advantage of the Florida hospital inpatient data is that it contains unique identifiers for the physicians of each inpatient, enabling me to merge patients with the characteristics and real estate holdings of their physicians. To obtain physician characteristics, I first link physicians to Florida's healthcare practitioner profiles using their professional license numbers. This data provides individual information such as full name, gender, and practice location for all medical doctors on file. I then supplement the practitioner profiles using the National Provider Identifier (NPI) registry of the National Plan and Provider Enumeration System (NPPES), which contains physician-level information including specialty, age, and graduation date.

To measure physicians' real estate holdings, I rely on CoreLogic, a real estate database tracking housing transactions based on county deed records. CoreLogic has good coverage of housing transactions since the mid-1990s and is also used by similar studies in the household finance literature (Bernstein et al., 2021; Aslan, 2022). For each deed record, CoreLogic provides the transaction date, sale price, property address, names of buyer(s) and seller(s), mortgage amount, and other house characteristics. To match physicians with their houses, I first restrict the house location to Florida and the house type to one of the following: single-family residence, condominium, commercial property, duplex, or apartment. I then search for houses ever purchased or sold by physicians in the inpatient sample, by matching buyer/seller names using a combination of "Last

Name + First Name + Middle Name Initial." Common names and physicians associated with more than three properties are excluded to reduce matching errors. A physician is identified as the owner of a matched house from the date of purchase until the date of sale (if the property is ever sold). Appendix B provides more details about this matching procedure.

To construct the final regression sample, I apply the following filters. I first consider medical doctors specializing in obstetrics and gynecology and exclude nurses and midwives. I then restrict the sample to physicians identified as homeowners by the end of 2006. I also only focus on physicians who practiced throughout the sample period and exclude inactive physicians whose number of deliveries is below the 1st percentile of all physicians. Finally, I drop patients whose physicians never performed C-sections during the sample period and those whose attending physicians differ from their operating physicians. This final step excludes physicians who lack the skill set to perform C-sections and therefore have to rely on external surgeons.

In the main analysis, I limit the sample period to the onset of the Great Recession (i.e., 2007–2009), when house values decreased most significantly. As an additional analysis to test whether the effects are symmetric, I also use the preceding years (i.e., 2004–2006), when house prices almost universally increased. Table 1 reports the descriptive statistics for both the analytical sample with matched physicians and the leave-out sample where the physicians are not matched. The matching procedures and filters outlined above identified 484 matched physicians who delivered a total of 187,873 births from 2007 to 2009.[8] Panel A of Table 1 shows that matched and unmatched physicians are fairly comparable with respect to the patients they attend, regardless of patient characteristics, individual risk factors, or aggregate risk factors.

Panel B of Table 1 shows that matched physicians are similar in terms of gender, tenure, workload, and C-section rate, compared to physicians with no matched properties. Regarding house characteristics, it is not uncommon for a matched physician to own multiple properties. By the end of 2006, 72% of the matched physicians owned one house, 21% owned two, and 7% owned three. 70% of all physicians have their primary houses in the same 3-digit zip codes as their main hospitals, and 69% have their primary houses in the same 3-digit zip codes where most of their patients reside. On average, physicians in the sample purchased their houses at a cost of $544,212 (in 2006 constant dollars) and had owned their houses for about five years by the end of 2006.

### III.B Measuring Financial Shocks to Physicians

The Great Recession provides a unique opportunity to study the role of physician financial health in their treatment choices. Characterized by a significant decline in house prices, the crisis caused substantial wealth shocks to homeowner physicians, deteriorating their financial health. To measure this shock stemming from the real estate market, I follow the household finance literature and use a measure of cumulative housing return since the time of purchase. Specifically, for a physician $j$ who bought a house in zip code $z$ at time $t_0$, their cumulative housing return measured at

[8] There are 368 unmatched physicians in the inpatient data. The match rate is therefore 57% and close to that in Bernstein et al. (2021) which uses a similar method to identify patent applicants' houses.

time $t$ is given by $R_{j,t} = \frac{HV_{j,t} - HV_{j,t_0}}{HV_{j,t_0}}$, where $HV_{j,t}$ represents the house value at time $t$. The market value of a house after purchase (i.e., $HV_{j,t}$ for $t > t_0$) is not documented in CoreLogic unless there are repeated sales, which are sparse in the data. Therefore, to measure subsequent house values, I use the Zillow Home Value Index for zip code $z$ at time $t$, $ZHVI_{z,t}$, as a proxy.[9]

When a physician owns more than one house, I calculate a weighted average cumulative housing return as shown in Equation (1) below.

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

Here, $\mathbf{Z}_j$ represents the set of zip codes where physician $j$'s houses are located. To avoid complications arising from strategic investment or divestment by physicians after the onset of the crisis, I fix each physician's $\mathbf{Z}$ at the end of 2006 and assume they hold the portfolio until the end of 2009 in the main analysis.[10] $w_z$ represents the weight of a house in zip code $z$ within the physician's portfolio, calculated using inflation-adjusted house price at the time of purchase.

The smaller the cumulative housing return, the more negative the financial shock experienced by a physician. For instance, an $R_{j,t}$ of $-20\%$ indicates that a physician has lost 20% of their house value relative to the purchase price. This measure has two advantages. First, behavioral economists have highlighted that investors evaluate gains and losses differently due to loss aversion (Tversky and Kahneman, 1991), with the purchase price serving as an important benchmark for homeowners (Genesove and Mayer, 2001). This preference is also relevant in my case as studies have found that physicians often target their income to specific reference points (Rizzo and Blumenthal, 1996; Rizzo and Zeckhauser, 2003). Second, cumulative returns have been shown to significantly predict negative home equity for homeowners (Gerardi et al., 2018; Dimmock et al., 2021), shedding lights on the possible channel of physician financial distress.

Compared to other market-level measures of house price movements, $R_{j,t}$ is less likely to be confounded by unobservables that simultaneously affect patient demand, as it incorporates two dimensions of physician-level heterogeneity. The first dimension stems from the zip code(s) in which physician $j$ resides, $\mathbf{Z}_j$. Physicians' houses are scattered in different zip codes. Appendix Figure A1 illustrates the number of physicians residing in each zip code across Florida. These zip codes exhibit varying house price movements, even during the same recession period (Bogin et al., 2019). Appendix Figure A2 shows the percentage changes in ZHVI across different zip codes in Florida during the sample period (2007–2009). The second dimension of heterogeneity arises from the timing of house purchases, $t_0$. Appendix Figure A3 shows that physicians purchased their houses in different years, with a long left tail in the distribution and over half of the physicians only becoming homeowners after 2000. This variation in purchase timing results in different levels

[9]ZHVI measures the typical value for homes in the 35th to 65th percentile range of a local market and is smoothed and seasonally adjusted. See `https://www.zillow.com/research/data/` for an introduction. ZHVI is only available from the year 2000. For values before 2000, I use the house price index provided by the Federal Housing Finance Agency (FHFA) to impute the missing data. Appendix B documents the details of this imputation.

[10]Results are robust when measuring housing return with time-varying portfolios, as shown in Appendix Table A5.

of housing return, even for physicians living in the same zip code, as they use different price levels as benchmarks. Appendix Figure A4 visualizes this variation by showing the distribution of simulated cumulative housing returns for physicians residing in different zip codes, assuming house purchases in 2000 and 2006, respectively.

Combining these two dimensions of physician-level heterogeneity, $R_{j,t}$ provides useful variation for identification, which I further discuss along with the econometric specification later. Figure 2 summarizes the distribution of $R_{j,t}$ across physicians and over time. For an average physician, cumulative housing return reached approximately 100% by the last quarter of 2006, suggesting that house values nearly doubled relative to the time of purchase. There is also substantial heterogeneity across physicians. By the same time, $R_{j,t}$ for physicians at the 25th and 75th percentiles were 40% and 148%, respectively. However, these premiums in house value were mostly wiped out by the end of 2009. The average physician entered the 2010s with only a 20% cumulative return. This drop in housing returns, caused by the recession, is substantial and highlights the magnitude of the negative shocks to physicians' financial status studied in this paper.

### III.C Econometric Model and Identification

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

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

where subscripts $i$, $j$, $h$, $c$, and $t$ denote patient, physician, hospital, patient's zip code, and time, respectively. The Florida hospital inpatient data are reported quarter by quarter — I therefore refer time $t$ to calendar year-quarter unless otherwise noted. On the left-hand side of Equation (2), $y_{i,j,h,t}$ represents the main outcome variable of interest in the case of childbirth, $1\{C - section\}_{i,j,h,t}$, a binary indicator which equals one if patient $i$ receives a C-section and zero if she receives a vaginal delivery. In addition to this measure of physicians' treatment choices, I also examine other margins that physicians can control during childbirth as well as maternal health outcomes such as length of stay and morbidity. On the right-hand side, $R_{j,t}$ represents the physician's housing return as of time $t$, as defined in Equation (1). To ease interpretation, I reverse the sign of $R_{j,t}$ in the regressions so that a *positive* estimate of $\hat{\beta}$ would support the hypothesis that physicians respond to negative wealth shocks by performing more C-sections.

This baseline specification controls for a comprehensive set of patient covariates, $\mathbf{X}_i$, including demographics (e.g., race and ethnicity), insurance types (e.g., Medicaid and commercial), weekend delivery, and 24 clinical risk factors measured by comorbidities observed before the start of labor (e.g., prior C-section, advanced maternal age, etc.). The inclusion of risk factors adjusts for the medical appropriateness of C-sections (versus vaginal delivery) and ensures that the analysis compares treatment choices between comparable patients. Detailed statistics for these covariates are reported in Table 1.[11]

[11]Similar risk factors are also used by previous studies (Henry et al., 1995; Gregory et al., 2002; Johnson and Rehavi,

Equation (2) also includes *physician* fixed effects, $\mu_j$, to account for time-invariant physician characteristics. Physicians could differ in their skills—-some may be better at performing C-sections or diagnosing patients in need of C-sections (Epstein and Nicholson, 2009; Currie and MacLeod, 2017). If such physicians systematically sort into areas where house prices decline the most, the effect of financial shocks could be overestimated. Physician fixed effects therefore help address this issue by controlling for physicians' practice styles and preferences that are persistent over time.

Finally, I include two additional sets of fixed effects to alleviate potential concerns of endogeneity. The first concern relates to an alternative supply-side channel parallel to physician responses. Specifically, existing studies have documented substantial variation in C-section rates across hospitals (Kozhimannil et al., 2013; Card et al., 2023; Robinson et al., 2024), and even found that hospital practices are also sensitive to financial shocks (Dranove et al., 2017; Adelino et al., 2022). If physicians experiencing greater financial shocks are more likely to work in hospitals with higher or lower C-section rates, or if they are affected by hospitals' incentives, the estimate of $\beta$ would also be biased. I therefore explicitly control for *hospital*$\times$*year-quarter* fixed effects, $\delta_{h,t}$, in Equation (2), which helps to separate supply-side responses at the individual physician level from that at the facility level.

The second concern arises from confounding demand shocks. For instance, existing research has shown that wealth or income shocks can affect households' healthcare utilization and spending (Acemoglu et al., 2013; Tran et al., 2023) or even impact households' physical and mental health (McInerney et al., 2013; Fichera and Gathergood, 2016; Schwandt, 2018). If highly-exposed physicians are more likely to see patients from recession-affected zip codes whose health conditions deteriorate, the estimated effect on physician behavior could be biased upwards. Fortunately, the inpatient data also provides patients' residence zip codes, so that I can additionally add *patient zip code*$\times$*year-quarter* fixed effects, $\phi_{c,t}$, into Equation (2). This helps to control for latent demand-side factors to a good extent, even if such unobservables are time-varying.

The identification of Equation (2) relies on the conditional independence assumption. That is, conditional on patient covariates, physician, hospital$\times$year-quarter, and patient zip code$\times$year-quarter fixed effects, patients' potential treatments are mean independent of physicians' housing returns. In other words, patients paired with different physicians should not differ systematically in terms of their observed characteristics. I assess this assumption by testing whether patient characteristics are balanced across physician housing returns. Specifically, I regress each of the patient characteristics in $\mathbf{X}_i$ on physician housing return, within all the fixed effects in Equation (2) included. Figure 3 presents the estimated coefficients for physician housing return from these individual regressions. These coefficients are generally close to zero and statistically insignificant, with only a few exceptions (e.g., obesity). Regressions of aggregate risk indicators, such as whether a patient is clinically flagged as low-risk, the Charlson Index, and the predicted C-section

2016; Currie and MacLeod, 2017; La Forgia, 2022). Appendix Table A1 shows that most of them are strong predictors of C-section risk.

risk, also yield consistent results. These findings indicate that patient characteristics are conditionally balanced across physicians with different housing returns, providing confidence in the conditional independence assumption.

The identification also assumes that, conditional on patient covariates and the fixed effects, other unobserved physician characteristics that may affect patient treatments are mean independent of physician housing return (i.e., the exclusion restriction). Although this assumption is difficult to test, it appears plausible for several reasons. First, by construction, physicians' housing portfolios are fixed before the onset of the Great Recession and are therefore unlikely to be correlated with factors that influence their treatment behavior *ex post*. While one might suspect that physicians could have anticipated the housing crisis and made strategic investment/divestment, 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). Second, physician fixed effects have accounted for variation in physician housing returns that is determined by the zip codes where physicians chose to live and the timing of their house purchases. The remaining *within-physician* variation is primarily driven by house price movement at more aggregate levels, and can be thought of as good as that from randomly exposing physicians to different extents of financial shocks in a quasi-experiment. Lastly, it is worth noting that the combination of physician fixed effects and year-quarter fixed effects (implicitly imposed by $\delta_{h,t}$ and $\phi_{c,t}$) absorbs other time-varying physician characteristics that are linear in time, such as physician age and years of work experience, even if these are not explicitly controlled for. Admittedly, the aforementioned controls cannot eliminate all potential sources of endogeneity. However, any remaining threats to identification must be correlated with physician housing returns in a time-varying manner.

Throughout the main analysis, I estimate Equation (2) using a linear probability model to allow inclusion of high-dimensional fixed effects and more straightforward interpretation of the coefficients. That said, Appendix Table A1 shows that results are robust to alternative non-linear models such as Logit. In addition, I cluster standard errors at the physician level for most regressions. Appendix Table A2 reports similar results when clustering at more conservative levels such as hospital, patient zip code, and physician zip code.

# IV Results

This Section provides the empirical results. I start by estimating the effect of physicians' financial health on the main treatment margin — vaginal delivery versus C-section — in subsection IV.A. This effect could be varying by physicians and unequal for different patients. I therefore explore these heterogeneities in subsections IV.B and IV.C. To better assess the consequences of physicians' responses on patient welfare, I examine the health impacts in subsection IV.D. Lastly, I report a battery of robustness checks in subsection IV.E.

### IV.A Effects on Physician Treatment Choices

Before delving into regression analysis, I provide model-free evidence on the relationship between physicians' housing returns and C-section rates. First, I residualize physicians' housing returns and C-section rates against physician fixed effects. The residualized observations are then grouped into ten equally sized bins based on physicians' housing returns, with average C-section rate calculated in each bin. Figure 4 visualizes this relationship between these two variables using a binscatter plot. The fitted line reveals that the C-section rate increases as physician housing return decreases, implying that physicians are more likely to perform C-sections when they experience greater losses in housing wealth .

To further explore how shocks to financial health affect physicians' treatment choices, I run linear regressions using patient-level data. The main outcome variable of interest is a dummy for whether patient $i$ receives a C-section as opposed to vaginal delivery from her physician, $\mathbf{1}\{C-section\}_i$. To simplify interpretation, I scale the outcome dummy by 100. The main independent variable is the physician's cumulative housing return, $R_{j,t}$, which is reversed in sign so that a positive estimate of $\beta$ indicates a higher C-section rate in response to negative housing shocks. Panel A of Table 2 reports the results, with fixed effects progressively added in the regression from the left to the right. Column (1) of Panel A includes patient covariates, year-quarter, and physician fixed effects. The coefficient before physician housing return is significantly positive, suggesting that a more negative financial shock is associated with a higher probability of C-section, holding all else constant. Column (2) additionally includes hospital×year-quarter fixed effects to control for hospitals' incentive and responses. The estimate becomes even larger in magnitude and more statistically significant.

A major concern of endogeneity is that higher C-section rates is not necessarily due to changes in physician behavior, but merely reflects that heavily shocked physicians attend riskier patients who demands C-sections. I have explicitly controlled for a rich set of patient characteristics in the regressions and shown that these characteristics are balanced across physicians (Figure 3). In other words, the effect so far is not likely driven by selection on observed patient characteristics. However, the role of selection on unobserved characteristics remains an open question. One such possibility is that patients, who are concurrently affected by the housing crisis, develop worse health conditions which justify more use of C-section. If patients' financial shocks are positively correlated with those of their physicians, the estimated physician response could be overstated.

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

Finally, C-sections could also be performed by the request of patients. To rule out the possibility that the result so far is driven by patient preferences, I examine the effects on unscheduled and scheduled C-section rates separately, since maternally requested C-sections are mostly scheduled in advance. Unscheduled C-sections are defined as those with ICD diagnosis codes indicating a trial of labor (Henry et al., 1995; Gregory et al., 2002). In Florida, approximately 77% of all C-sections are scheduled, although not all of them are maternally requested. I hypothesize that the housing shock will have a weaker effect on scheduled C-sections compared to unscheduled cases. Columns (4) and (5) of Table 2 use unscheduled and scheduled C-section probabilities as outcome variables, respectively.[12] Physician housing return significantly affects the unscheduled C-section rate but not the scheduled rate, implying that the increase in C-section rate concentrates in cases where patient preferences play a minimal role.

In Panel B of Table 2 and much of subsequent analyses, I replicate the results using a subsample of *low-risk* patients. Following the guidelines of the Agency for Healthcare Research and Quality (AHRQ), low-risk patients are defined as those with no indication of prior C-section, hysterotomy, abnormal presentation, preterm delivery, fetal death, multiple gestation diagnoses, or breech birth.[13] Low-risk patients are generally considered good candidates for vaginal delivery, making additional C-sections in this group more likely to be medically unnecessary and a concern for public health (Hartmann et al., 2012). Compared with those in Panel A, the estimated effects among low-risk patients are more significant statistically and larger in magnitude. Take Column (3) of Panel B ($\hat{\beta}$=3.130) as an example — a one-standard-deviation decrease in physicians' cumulative housing returns ($\approx 0.65$) leads to an increase of 2 percentage points in the low-risk C-section rate, which is equivalent to a 9% increase relative to the mean. Putting together, these results help further rule out the potentially confounding demand-side channel.

### IV.B Heterogeneous Effects by Physician Characteristics

The effect of financial health on physician treatment choices can vary across different physicians. This section therefore examines the heterogeneity in physicians' responses by highlighting the role of three relevant characteristics: (1) physician practice styles, (2) physician competition, and (3) physician gender.

I first investigate how physicians' responses depend on their ex ante practice styles. Previous 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 examining whether the increase in C-section rates primarily comes

[12] In Column (4), the dependent variable takes 1 for unscheduled C-section and 0 otherwise (including unscheduled C-section and vaginal delivery). The scheduled C-section rate is constructed similarly in Column (5).

[13] See AHRQ's Inpatient Quality Indicator 33 (IQI 33): https://qualityindicators.ahrq.gov/Downloads/Modules/IQI/V2020/TechSpecs/IQI_33_Primary_Cesarean_Delivery_Rate_Uncomplicated.pdf. The same criteria for low-risk births is used by La Forgia (2022). I also try an alternative definition of low-risk births using cutoffs based on predicted C-section probability, which gives similar results.

from physicians who have already been using more C-sections ex ante or those who have not. I first define a measure of *excessive* C-section rate for each physician, which is calculated as the difference between the actual C-section rate and the predicted C-section rate prior to the shocks.[14] Columns (1) and (2) of Table 3 report the results in two subsamples based on whether the physician's excessive C-section rate is above or below the median. Physicians with a lower excessive C-section rate are more likely to increase their C-section rates in response to lower housing returns. This finding provides evidence that physician practice styles could change over time, and also suggests that C-section rates across different providers likely converge during times of negative financial shocks.

Next, I investigate whether the estimated effect varies by the landscape of market competition. This effect is ex ante unclear — competition could either put pressure on physicians' profits, incentivizing stronger responses to financial shocks, or create constraints on physicians' behavior, deterring inappropriate treatment choices. I follow previous literature and utilize the variation in physician density of a local market to measure physician competition (Gruber and Owings, 1996; Baicker et al., 2006). Specifically, physician density is defined as the number of OB/GYNs scaled by the number of births in a county and fixed at the year 2006. Patients are then divided into two groups based on whether they reside in lower-density or higher-density physician markets. Results in Columns (3) and (4) of Table 3 show that the effect is stronger in low-density markets, consistent with the possibility that physicians in these markets are less disciplined by market competition and therefore more capable of adjusting their practice styles. This finding adds to the literature on how physician competition might shape physician-induced demand by examining a specific scenario where physicians are in different financial health (Dunn and Shapiro, 2018; Brekke et al., 2019; Ikegami et al., 2021).

Lastly, I investigate if physician gender plays a role in affecting the treatment choices. On the one hand, existing work has provided evidence that female physicians tend to work less because of more commitments outside of work (Pruckner et al., 2025), and more likely to adopt less aggressive treatment options (Currie et al., 2016). On the other hand, since all childbirth patients are female, the gender effect also entails the potential advantages of gender concordance between patient and physician, which could stem from more empathy and better communication. For example, Cabral and Dillender (2024) and Greenwood et al. (2018) have found that female patients are more likely to be receive favorable evaluations and have lower mortality rates from physicians of the same gender. In my data, 59% of OB/GYNs are female, who deliver about 56% of all births. Results in Columns (5) and (6) of Table 3 show that patients are more likely to receive C-sections when their female physicians are financially shocked, suggesting that gender concordance does not generate overwhelming benefits. That said, it is also important to keep in mind that female physicians could have greater constraints in working time and greater sensitivity to financial shocks.

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

## IV.C Heterogeneous Effects by Patient Characteristics

The effect of financial health on physician treatment choices can also be unequal for different patients. Understanding the distributional effects is important to evaluate the consequences of physician behavior on patient welfare and design more targeted policies. In this section, I highlight the role of two patient-side factors that have been extensively examined in the healthcare literature: (1) expected benefit, or appropriateness, of receiving a C-section, and (2) patient's race and ethnicity.

How patient welfare is affected by physician financial shocks hinge on whether the affected patients are indeed suitable for C-sections. Intuitively, physicians are likely to have already performed C-sections on patients who would benefit the most, but may be less inclined to do so for those with minimal expected benefits. In other words, patients with medium-level benefits are more likely to be shifted between the two treatments. To test this prediction, I first use all patients in the analytic sample and estimate a Logit regression model including a binary variable of C-section as outcome and all detailed risk factors as predictors.[15] The predicted value from this model is termed the "appropriateness" for each patient to receive a C-section. This approach effectively assumes that physicians have performed the "correct" number of C-sections on average (Currie and MacLeod, 2017; Robinson et al., 2024).

Columns (1) to (3) of Table 4 show the estimates separately for three equally sized groups: patients with low-, medium-, and high-appropriateness of C-section. As is expected, the effect is most significant among medium-appropriateness patients, with the magnitude being more than two times than for the low-appropriateness group and more than three times larger than for the high-appropriateness group. Note that the "appropriateness" measure does not necessarily correlate with the "low-risk" indicator used in subsetting the samples (i.e., Panel B in most tables), as the former take into account risk factors more than the "low-risk" flags. In fact, the same results can be found even among low-risk patients in Panel B of Table 4.

To study if the effect varies by patient race and ethnicity, I run regressions on three groups of patients — non-Hispanic Black, Hispanic, and others — respectively. Columns (4) to (6) of Table 4 report these estimates. The effect is most significant for non-Hispanic Black patients, with the magnitude being more than twice than the average effect estimated in Table 2. Specifically, a one-standard-deviation decrease in physician housing returns results in a 4.3 percentage point increase (or 11%) in the C-section rate among non-Hispanic Black patients. Effects for other patients, although remaining in the same sign, are less precisely estimated. This finding is consistent with that in the literature — Black patients are more susceptible of provider discretion, all else equal. For example, Singh and Venkataramani (2022) shows that Black patients tend to wait longer, receive less care from physicians, and eventually have higher mortality rates when hospitals are approaching capacity constraint. Also in the context of Childbirth and thus closer to this paper, Corredor-Waldron et al. (2024) find a gap in C-section rates between non-Hispanic Black and other patients, which disappears when the costs of ordering unnecessary C-sections are higher.

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

My finding adds to this stream of evidence by emphasizing the possibility that racial disparity in healthcare could be widened in times when provider financial health is worsened.

### IV.D Effects on Patient Health

The previous sections have shown that negative shocks to physicians' financial health influence their treatment choices, with patients of disadvantaged socio-economic status (e.g., Black patients) bearing the greatest costs. To provide a more comprehensive picture on the effect on patient welfare, this section explores if the changing physician behavior has any material impact on a variety of maternal health outcomes.

The theory has given ambiguous predictions on this issue. Patient health outcomes can be worse off if wealth losses from declining house values incentivize physicians to adopt more profitable procedures, potentially leading to over-treatment that deviates from the clinical optimum. The opposite is also possible when physicians under financial distress seek to minimize potential adverse outcomes by resorting to more defensive treatment. At the same time, as is shown in Section IV.C, the patients most affected are those closer to being indifferent between cesarean and vaginal deliveries (i.e., the "marginal" patients). Since the benefits and costs of C-sections for these patients are less clear, whether the higher C-section rate would have an economically significant effect on health outcomes remains an empirical question.

I focus on two sets of measure of maternal health outcome. The first relates to the number of days a patient stays in the hospital (i.e., from the date of admission to the date of discharge). I preserve the baseline specification in Equation (2) and use the natural logarithm of one plus the total length of stay as the dependent variable.[16] Column (1) of Table 5 reports the result — patients' length of stay tends to increase as a result of physician financial shocks. Specifically, a one-standard-deviation decrease in physician housing returns increases the length of stay by 0.5%, or approximately 0.013 days. While small in magnitude, this estimate is comparable to findings in previous work. For instance, Card et al. (2023) report that delivering in a high-cesarean-rate hospital increases the total length of stay by a similar extent.

To explore what drives the increase in length of stay, Columns (2) and (3) of Table 5 divide the total number of days stay into two components: pre-delivery stay (i.e., the number of days from admission to delivery) and post-delivery stay (i.e., the number of days from delivery to discharge). For an average patient, the total length of stay is 2.54 days, with 0.29 days pre-delivery and 2.25 days post-delivery. The increase in overall length of stay is primarily driven by longer post-delivery stays, which is consistent with more use of C-sections, as they typically require longer recovery times. It also suggests that physicians do not respond by encouraging more scheduled C-sections, because otherwise post-delivery stays would have been significantly shorter.

To better understand the effect on the distribution of patient inpatient stay, I also define a binary indicator for prolonged length of stay, which equals one if the total stay exceeds 4 days

[16]Poisson regressions using integer count data as the outcome produce similar results.

for cesarean births or 2 days for vaginal births, and zero otherwise. In the raw data, approximately one-fifth of all patients experience prolonged inpatient stays. Regression results using this indicator as outcome variable are reported in Column (4) of Table 5. Conditional on patient characteristics, the probability of prolonged stays significantly decreases as physician housing returns decline. Specifically, a one-standard-deviation decrease in physician housing returns reduces the probability of prolonged stays by about 1 percentage point, or 5% relative to the mean. This finding suggests that, although higher C-section rates increase length of stay on average, a subset of patients might have benefited, probably from being assigned to more appropriate treatments.

Next, I examine a series of maternal morbidity, or complications occurred during and immediately after the process of labor and delivery. Following previous studies (Johnson and Rehavi, 2016; Freedman and Hammarlund, 2019; La Forgia, 2022), I code the following four types of maternal morbidity using ICD codes: hemorrhage, infection, laceration, and severe maternal morbidity. The first two types, hemorrhage and infection, could occur in both cesarean or vaginal births. The third type, laceration, is typically associated with vaginal deliveries only. The fourth type, severe morbidity, is less common and includes negative events such as sepsis, eclampsia, anesthesia complications, and others that require additional procedures such as hysterectomy and blood transfusion (Callaghan et al., 2012; Kilpatrick et al., 2016). More than 5% of patients in my data experience one or more of these complications.[17]

As is shown in Columns (5) to (8) of Table 5, physician financial shocks do not significantly affect maternal morbidity, at least for the four morbidity measures considered here. These results, along with those related to length of stay, remain consistent even in the low-risk subsample, as shown in Panel B of Table 5. Overall, I find no decisive evidence that physicians' responses to negative financial shocks substantially impact maternal health. If anything, higher C-section rates prevent patients from entering prolonged inpatient stays, but not at a cost of significantly longer length of stay or higher complication rates. These results hint on the motives of defensive medicine behind physician behavior, which I will further discuss in Section V later. That said, it is important to note that patients receiving C-sections may face additional hardship that is not captured in my data, such as longer-term reproductive costs (e.g., repeated C-sections) and mental health issues (e.g., postpartum depression). Due to data limitations, I am also unable to measure health impacts on infants.

### IV.E Robustness

Results of several additional robustness checks are summarized in Appendix Tables A3 to A5. I first add an extended set of fixed effects on top of the baseline specifications, ruling out the possibility that the main result is driven by some other selection mechanisms. I then consider a range of

[17]One might worry that the Florida inpatient discharge data under-reports these complications, as the morbidity rates are slightly lower than those reported by Johnson and Rehavi (2016), although they use data in California. Another outcome to consider is in-hospital mortality, which, unfortunately, is even more scarce in the Florida data, with a rate of approximately 4 per 100,000 women. Given these reasons, one should probably consider the health effect here as a conservative estimate of the true effect.

alternative measures of physician financial shocks, all of which have produced qualitatively similar results. Finally, I show that the main result is not sensitive to certain specifications of sample construction.

**Ruling Out Other Selection Channels.** Previous sections have attempted to rule out alternative explanations from both supply-side and demand-side by conditioning the identification on a rich set of patient covariates, physician, hospital×time, and patient ZIP code×time fixed effects. However, there remains a nuanced possibility that patients have unobserved preferences for and thus self-select into certain providers. If such providers happen to experience greater or smaller housing wealth shocks, the main result could be biased.

I first examine whether *patient-hospital* matching may drive the main results. I focus on a subset of patients who live close to the hospitals where they deliver and restrict the distance between a patient's residential zip code and her hospital's zip code to no more than 10 miles. These patients are more likely to choose the focal delivery hospitals based on geographical convenience rather than other confounding factors. Column (1) of Appendix Table A3 shows that the estimate remains highly significant within this subsample. To address the same concern, I also try to additionally include patient zip code×hospital fixed effects, which control for time-invariant factors within each patient zip code–hospital pair. Column (2) of Appendix Table A3 shows that the results are consistent with the baseline estimates.

Next, I consider the possibility of *patient-physician* matching. Specifically, I focus on a subset of patients who live far away from their physicians by requiring the patient's 3-digit zip code to differ from that of her physician. These patients are arguably less likely to have a prior relationship with their physicians or have knowledge of their physicians' financial health ex ante. Column (3) of Appendix Table A3 shows that the results remain robust for this group of patients. Similarly, I include patient zip code×physician fixed effects, with consistent findings reported in Column (4) of Appendix Table A3.

Finally, *physician-hospital* matching also matters, as previous work such as Mourot (2024) has found that physician performance could be hospital-specific. In reality, this may be due to physicians' hospital privileges, employment affiliation, or other factors in their production functions. The policy implications would differ if the results merely reflected physicians performing more C-sections at certain hospitals as opposed to an overall shift in their practice styles. To alleviate this concern, Column (5) of Appendix Table A3 restrict to a subset of physicians who only practice in one hospital during the sample period (i.e., "single-homing" physicians). Column (6) additionally includes physician×hospital fixed effects in the regression. Results in both columns remain similar.

**Alternative Measures of Physician Financial Shocks.** In the main analysis, I measure physicians' financial shocks using their cumulative housing returns since purchase. Here, I consider four alternative measures. First, one might worry that physicians' responses to real estate shocks are not instantaneous. I therefore try to use the same cumulative housing return since purchase but *lagged by one quarter* as the main independent variable. Column (1) of Appendix Table A4 reports the result using this lagged measure. The estimate remains significant and closely aligns with the baseline results.

Second, physicians might place a greater weight on more recent changes in housing returns. To capture this, I use the cumulative housing return over the past quarter as a measure of housing wealth shocks. Column (2) of Appendix Table A4 shows that a decrease in this *quarter-over-quarter* return also significantly predicts an increase in C-section rates. I also try to further lengthen the period during which physician housing returns are measured and construct a *year-over-year* return, which is also used in related work such as Bernstein et al. (2021) and Dimmock et al. (2021). The result, shown in Column (3) of Appendix Table A4, is once again consistent with the hypothesis. Note that both quarterly and annual returns are arguably less affected by the timing of a physician's house purchase, suggesting that the house locations (i.e., zip codes) alone can provide useful variation in their subsequent housing returns.

Lastly, I use the logged level of *house prices* as the main independent variable in the regression. House prices are predicted as the (inflation-adjusted) purchase price multiplied by the cumulative housing return. Column (4) of Appendix Table A4 reports the result — C-section rates increase as physicians' house prices decrease. The coefficient before the logged house prices can also be interpreted as the semi-elasticity of C-section rate. For example, in the low-risk subsample, a 10% decrease in house prices results in a 0.3 percentage-point increase in C-section rates.

**Alternative Sample Specifications.** In the main analysis, I have focused on physicians who remained actively practicing throughout the sample period and are less subject to employment/unemployment shocks besides wealth shocks. However, physicians who are at earlier or later stages of their careers may exhibit different preferences and behavior. Does the result depend on these physicians? I try to allow for physician turnover by including physicians who entered the labor force after the recession began in 2007 (i.e., late entries) as well as those who retired before the recession ended in 2009 (i.e., early exits). These results, reported in Columns (1) to (3) of Appendix Table A5, show little change compared to the baseline estimates.

Also recall that I fix each physician's housing portfolio as of the end of 2006 when constructing their housing returns and assume they hold the portfolio until the end of 2009. Because of this restriction, the main analytic sample only includes physicians identified as home owners on later than 2006. However, it is possible that some physicians only purchased homes after the crisis began or sold their houses before the crisis ended. To test if results are sensitive to inclusion of these physicians, I allow for time-varying home ownership instead and track physician housing returns accordingly. The results, reported in Columns (4) to (6) of Appendix Table A5, remain remarkably similar.

# V Discussion

So far in the paper I have used physicians' housing returns to measure their financial health and shown that they are more likely to adopt C-sections as financial health worsens. However, lower housing returns can trigger such behavioral responses in more than one possible mechanisms. For example, declining housing wealth increases physicians' marginal utility of income, motivating them to profit from performing more C-sections. At the same time, lower house equity makes physicians more vulnerable to bankruptcy or future income loss, leading physicians to opt for C-sections to avoid potential malpractice liability. Understanding which of these mechanisms underlies the higher C-section rate is crucial for result interpretation and policy implications.

In what follows, I first introduce a simple conceptual framework in Section V.A to reconcile the empirical results documented in previous sections. This framework accounts for three important motives behind physicians' treatment choices: financial incentives, malpractice concerns, and patient welfare. It showcases the aforementioned mechanisms through which financial shocks could affect C-section rates. Next, in Section V.B, I provide additional evidence to distinguish these mechanisms, following the predictions of the conceptual framework.

## V.A Conceptual Framework

As is discussed in Section II, physician discretion plays an important role in the clinical setting of childbirth. The following conceptual framework therefore abstracts away from the "negotiation" between physicians and patients, and assume that patients follow physicians' recommended treatment. Note that this is not to exclude patients' interest from the decision-making process. Instead, I adopt the typical setup in the healthcare literature and assume that physician agents are altruistic and take into account patient welfare in their own utility maximization problems (McGuire, 2000). Although the physician here is an obstetrician/gynecologist, this conceptual framework can be extended to other settings outside of childbirth where a physician chooses from a set of treatment options, such as cardiologists deciding whether a heart attack patient should receive open-heart surgery (e.g., coronary artery bypass grafting, CABG) or minimally invasive intervention (e.g., percutaneous coronary intervention, or PCI).

**The Physician's Problem.** I first outline a physician $j$'s utility from treating a childbirth patient $i$. The physician's utility consists of three motives: (1) personal earnings from physician fee (i.e., financial incentives), (2) expected costs caused by malpractice claim (i.e., malpractice costs), and (3) medical benefits to the patient (i.e., physician altruism). All three components are dependent on the specific treatment $k \in \{v, c\}$ that the physician chooses to maximize their utility, where $v$ and $c$ denote vaginal delivery and C-section, respectively.

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

The first component, $f_j(\omega_k)$, captures the pecuniary utility for physician $j$ from providing treatment $k$, within which $\omega_k$ represents the reimbursement physician fee. As is discussed in Section II, physician fees for C-sections are on average higher than for vaginal deliveries (i.e., $\omega_c > \omega_v$). $f_j(\cdot)$ is assumed to have diminishing marginal utility, meaning that the wealthier the physician, the less additional utility they derive from an extra dollar of income. One example of such a functional form 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 the initial wealth level of physician $j$, and $\gamma$ is the coefficient of relative risk aversion.

The second component, $m_j(\tau_k)$, captures the expected cost of malpractice. C-sections are commonly viewed as a form of defensive medicine, associated with a lower probability of malpractice litigation (i.e., $\tau_c < \tau_v$). Conditional on being sued and found liable, the physician has to pay a liability cost of $L$, as well as an additional cost $D_j$ that is only turned on when physician $j$'s financial health is extremely poor. A typical example of $D_j$ is the potential cost of bankruptcy, incurred if the physician's personal wealth is too little to cover the liability (i.e., $D_j = D \cdot \mathbf{1}\{W_j < L\}$). Alternatively, $D_j$ may reflect reduced future earnings because of reputational damage (MacLeod, 2007), which is particularly overwhelming for financially distressed physicians. Put together, the expected malpractice costs can be expressed as $m_j(\tau_k) = \tau_k(L + D_j)$.[18]

The last component, $b_k(X_i)$, denotes the medical benefits that patient $i$ with characteristics $X_i$ would have received from treatment $k$. A larger $b_k(X_i)$ indicates that treatment $k$ is relatively more appropriate for patient $i$, and therefore, choosing a treatment other than $k$ imposes greater disutility on the physician. This disutility may arise from physicians' "internal conscience," as they are assumed to be altruistic.

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

$$b_v(X_i) - b_c(X_i) \leq \big[f_j(\omega_c) - f_j(\omega_v)\big] - \big[m_j(\tau_c) - m_j(\tau_v)\big] \tag{4}$$

$b_i$ on the left-hand side of (4) represents the differential medical benefits for patient $i$ to receive a vaginal delivery over a C-section (or the "appropriateness" of vaginal delivery). $f_j(\omega_c) - f_j(\omega_v)$ and $m_j(\tau_c) - m_j(\tau_v)$ on the right-hand side are the differences in physician's pecuniary earnings and expected malpractice costs between C-sections and vaginal deliveries, respectively. A C-section is chosen if its "unattractiveness" of financial incentives and malpractice risks is sufficiently large to offset the medical benefit of vaginal delivery. Or, $b_v(X_i) - b_c(X_i)$ represents the maximum utility the physician is willing to forgo by not performing a C-section.

Assuming that $\mathbf{B}(\cdot)$ is the inverse CDF of $b_v(X_i) - b_c(X_i)$, the probability of patient $i$ receiving a C-section can be written as

$$p_i = \mathbf{B}\Big(\big[f_j(\omega_c) - f_j(\omega_v)\big] - \big[m_j(\tau_c) - m_j(\tau_v)\big]\Big) \tag{5}$$

[18] There could be other costs associated with different treatment options, which for simplicity can be thought of already been adjusted in $\omega_k$.

**The Role of Physician Financial Shocks.** For the purpose of this paper, physician fees $\omega_k$, malpractice risks $\tau_k$, malpractice liability $L$ are all treated as exogenous parameters. For a given patient (i.e., conditional on patient characteristics $X_i$), negative financial shocks (e.g.,, exogenous decrease in $W_j$) can give rise to a probability of a C-section through two distinct mechanisms.

The first mechanism operates through $f_j(\omega_c) - f_j(\omega_v)$. Using the example of CRRA utility function, it is easy to see that $\frac{\partial f_j^2(\omega_k)}{\partial \omega_k \partial W_j} = -\gamma(W_j + \omega_k)^{-\gamma-1} < 0$. In other words, as physicians' housing wealth decreases, their marginal utility of income increases, which in turn motivates them to earn additional profits. As a result of this financial incentive, the probability of C-section increases — a mechanism which I call the *wealth effect*.

The second mechanism arises from $m_j(\tau_c) - m_j(\tau_v)$. As a physician's housing equity declines to a low enough level, their ability to absorb bankruptcy costs or future income losses associated with malpractice liability diminishes. In these scenarios, the legally safer treatment option becomes increasingly more attractive to financially constrained physicians, increasing the likelihood of choosing a C-section. This is referred to as the *financial distress* mechanism.

This conceptual framework predicts that the mechanism of financial distress is muted when the physician's wealth increases from a ex ante safe level. On the contrary, the wealth effect is always in play no matter under positive or negative wealth shocks. Moreover, the financial distress mechanism is supposed to be stronger for physicians whose financial capacities are limited. Designed around these predictions, I provide several sets of additional evidence to distinguish the relative importance of the aforementioned mechanisms in the next section.

## V.B Distinguishing the Mechanisms

**Asymmetric Effects.** One of the properties of the financial distress mechanism is that it is more salient when physicians experience negative financial shocks. Intuitively speaking, bankruptcy costs and future income losses, potentially resulted from malpractice liability, are less relevant when the physician keeps accumulating wealth. The wealth effect, on the contrary, predicts that physicians should perform fewer C-sections even when they experience positive financial shocks. In other words, the effect of physician financial health would be asymmetric for positive and negative shocks if the financial distress mechanism dominates the wealth effect, and asymmetric if the other way around.

As opposed to the main analysis which has used a sample period from 2007 to 2009 when the Great Recession set in, I extend the time frame forward and repeat the analysis using data from three pre-crisis years (2004–2006). During this period, nearly all zip codes experienced an increase in property prices. This trend is illustrated in Figure 2, which shows that the average cumulative housing return across all physicians was below 25% at the beginning of 2004 but rose to approximately 90% by the end of 2006. Columns (1) to (3) of Table 6 report the regression results which preserve all specifications from Equation (2). Estimates for this alternative sample period are statistically insignificant, no matter for the average, unscheduled, or scheduled C-section rates.

The null results persist even in the sample of low-risk births, as is shown in Panel B of Table 6.

Similarly, a body of empirical studies also find that households tend to respond more strongly to negative real estate shocks, while their responses to positive shocks are muted (Bernstein, 2021; Bernstein et al., 2021; Aslan, 2022). This finding also echos the behavioral theory of loss aversion (Tversky and Kahneman, 1991; Genesove and Mayer, 2001), which posits that individuals weigh losses more than equivalent gains. The asymmetric nature of physicians' responses to financial shocks perhaps partially explains why C-section rates remain stubbornly high even after the crisis, because providers are less concerned about bankruptcy risks or lost earnings in economic upturns.

**Physicians' Loan-To-Value Ratios.** Physicians in greater debt are economically more vulnerable and therefore have greater financial distress. The conceptual framework predicts that these physicians are more likely to adopt legally safer treatments, anticipating potential malpractice costs. Building on this idea, I hypothesize that the effect of negative housing shocks is larger for physicians on the verge of negative housing equity.

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

Following Bernstein et al. (2021) and Dimmock et al. (2021), I define a physician as deeply in debt if their current LTV ratio is equal or greater than 90%. Columns (4) to (6) of Table 6 report the results using a subsample of patients whose physicians have high LTV ratios. Similar to the main results, negative housing shocks significantly predict higher average and unscheduled C-section rates but not the scheduled C-section rate. The estimates are about three times larger in magnitude compared to the average result in Table 2, lending support for the financial distress mechanism being important in explaining physicians' responses.[19]

**Effects on Other Treatment Margins.** If it is were the case that physicians act in fear of malpractice costs, one should expect that they not only increase C-section rates but also adopt other defensive treatments. I therefore examine a set of other treatment margins, along which physicians might respond had they practiced more defensively in financial distress.

I start by looking into induction, which is used to stimulate uterine contraction and facilitate vaginal birth when the health of the mother or fetus is at risk. One might wonder whether physicians would increase induction rates to avoid potential complications in a prolonged first-stage labor. Column (1) of Table 7 reports the results using an indicator for whether a patient is induced as the dependent variable. The estimate is statistically insignificant, indicating that physicians do

[19]Subsample results for low-LTV physicians, available upon request, are less significant both statistically and economically.

not appear to intervene early in the labor and delivery process. This is understandable as induction does not guarantee a safe outcome — an adverse event can still be blamed on the physician's decision to "wait and see."

I then study assisted procedures which could be used in the second stage of labor to assist vaginal delivery. Two examples of such assisted procedures are the use of vacuum devices and forceps. Column (2) of Table 7 uses an indicator for vacuum/forceps use as the outcome and finds that patients are more likely to receive these procedures when physician housing returns decrease. Given that the use of these assisted procedures does not increase physicians' reimbursements, this finding likely suggests defensive medicine — physicians attempted less invasive options and tried everything reasonable before resorting to surgery. Even if these assisted procedures fail, the record could protect them from being accused of "rushing to a C-section" or "doing nothing."

There could also be other treatment margins not captured by the use of C-sections, induction, or assisted procedures. For instance, patients might undergo additional tests even after the labor and delivery process, including extra monitoring, blood tests, or other medical interventions. To investigate these margins, I follow Johnson and Rehavi (2016) and use the total dollar amount of hospital charges as a summary measure of overall treatment intensity. Column (3) of Table 7 reports the estimate using logged hospital charges as the dependent variable. Hospital charges significantly increase as physician housing returns decrease. Specifically, a one-standard-deviation decrease in physician housing returns leads to a 1.5% increase in hospital charges, equivalent to a \$194 increase for an average patient.

Lastly, I explore the effect on the number of births delivered by each physician in a given period (i.e., the extensive margin). One might expect that physicians can also respond to negative financial shocks by treating more patients in an effort to compensate for wealth losses. To test this possibility, I regress the number of deliveries on physician housing return using an aggregated physician$\times$year$\times$quarter-level data set, controlling for physician and year$\times$quarter fixed effects. The estimate from a Poisson model is reported in Column (4) of Table 7. The insignificant result implies that the wealth effect likely plays a limited role in physicians' decisions.

To summarize, the asymmetric effects for positive and negative shocks, the larger effects for highly-leveraged physicians, and the use of other defensive treatments all support financial distress being a major mechanism through which physicians' financial health affects their treatment choices. Moreover, physicians' responses appear to be concentrated more on the intensive margin as opposed to the extensive margin. These findings are also not completely ruling out the wealth effect, although back-of-the-envelope calculations suggest that the physicians were only able to recoup a small fraction of their wealth losses through higher C-section rates.[20]

[20] Combining the average number of deliveries per physician in Table 1 and the coefficient in Column (3) of Table 2, I estimate that a physician would deliver about two more C-section births per year, or recoup about \$1,000. This amount is unlikely to cover the loss in housing wealth but is indeed consistent with the finding in Gruber and Owings (1996).

# VI Conclusion

This paper examines how physicians' financial health influences their treatment decisions and patient health outcomes. I leverage a novel dataset that links physicians' real estate holdings with their clinical behavior and exploit within-physician variation in housing returns induced by the Great Recession. In the context of childbirth, I find that physicians increase their use of C-sections in response to negative housing wealth shocks. This effect is most pronounced among physicians who previously performed fewer excessive C-sections, those practicing in less competitive markets, and female physicians. Patients who are more likely to be affected include those with moderate expected benefits from C-sections and non-Hispanic Black patients. However, I find no decisive evidence that patient health outcomes are substantially affected — patients experience longer length of stay on average but are slightly less likely to experience prolonged hospital stays, with no meaningful changes in morbidity rates.

I interpret these findings through a conceptual framework that incorporates financial incentives, malpractice concerns, and patient welfare as key drivers of physician decision-making. The framework identifies two channels through which negative financial shocks may encourage more C-sections: the wealth effect and financial distress. My empirical results point to financial distress as the dominant mechanism, as physicians probably use C-sections as a strategy of defensive medicine to mitigate malpractice costs when their financial capabilities are limited. Specifically, physicians do not respond to positive wealth shocks, but respond more strongly when LTV ratios are higher. I also find evidence consistent with defensive medicine in other treatment margins: physicians increase the use of assisted procedures, but do not deliver more babies in total. Although I do not find strong evidence for a wealth effect, it is also important to recognize that avoiding malpractice liability is unlikely to be the only motive. The role of other factors, such as borrowing constraints (Aladangady, 2017; Cloyne et al., 2019) and psychological costs (Currie and Tekin, 2015; Engelberg and Parsons, 2016), is left for future research to explore.

Regarding policy implications, this paper speaks to the effectiveness of federal programs aimed at improving physicians' financial resilience (e.g., the Public Service Loan Forgiveness program and the Income-Driven Repayment plan). My results suggest that these programs may prevent physicians from sliding into financial distress and, in doing so, support healthcare delivery. The weak evidence for a pure wealth effect also aligns with prior research showing that substitution effects often dominate income effects in physician behavior — reinforcing the importance of physician payment regulation. Finally, this paper sheds light on how financial market frictions can spill over into clinical decision-making. While I focus on housing wealth shocks, real estate is not the only source of financial risk. Other shocks, such as stock market volatility, may also affect physicians' behavior, particularly in a shorter horizon. Investigating how physicians respond to higher-frequency financial shocks represents an interesting direction for further studies.

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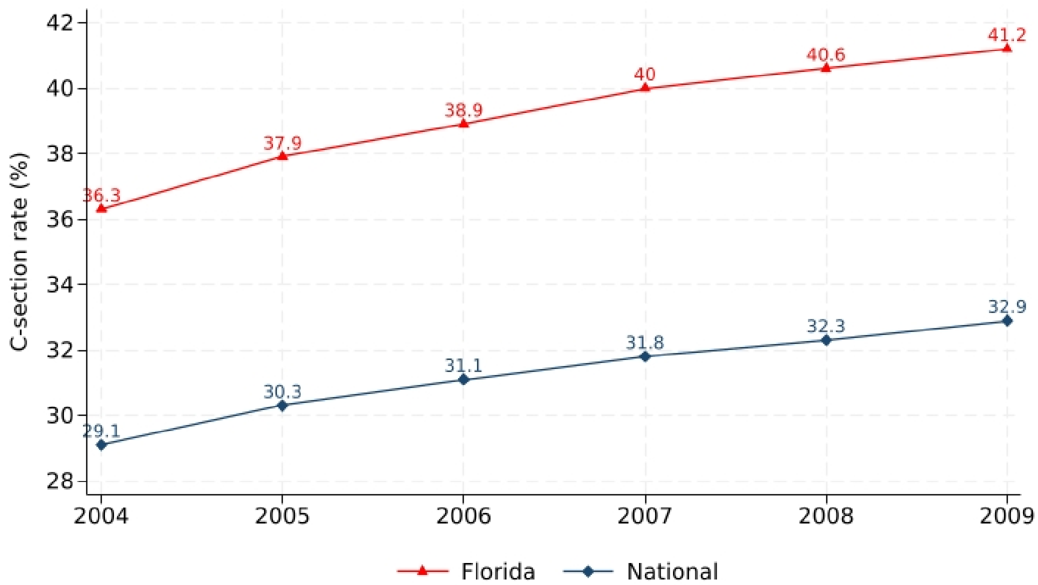
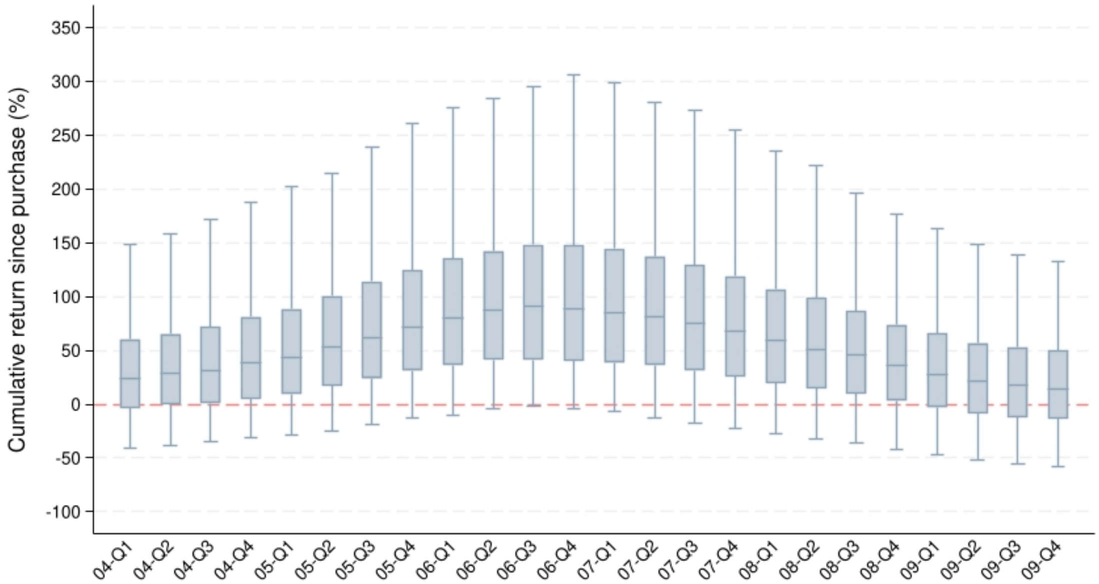
## Figures and Tables

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



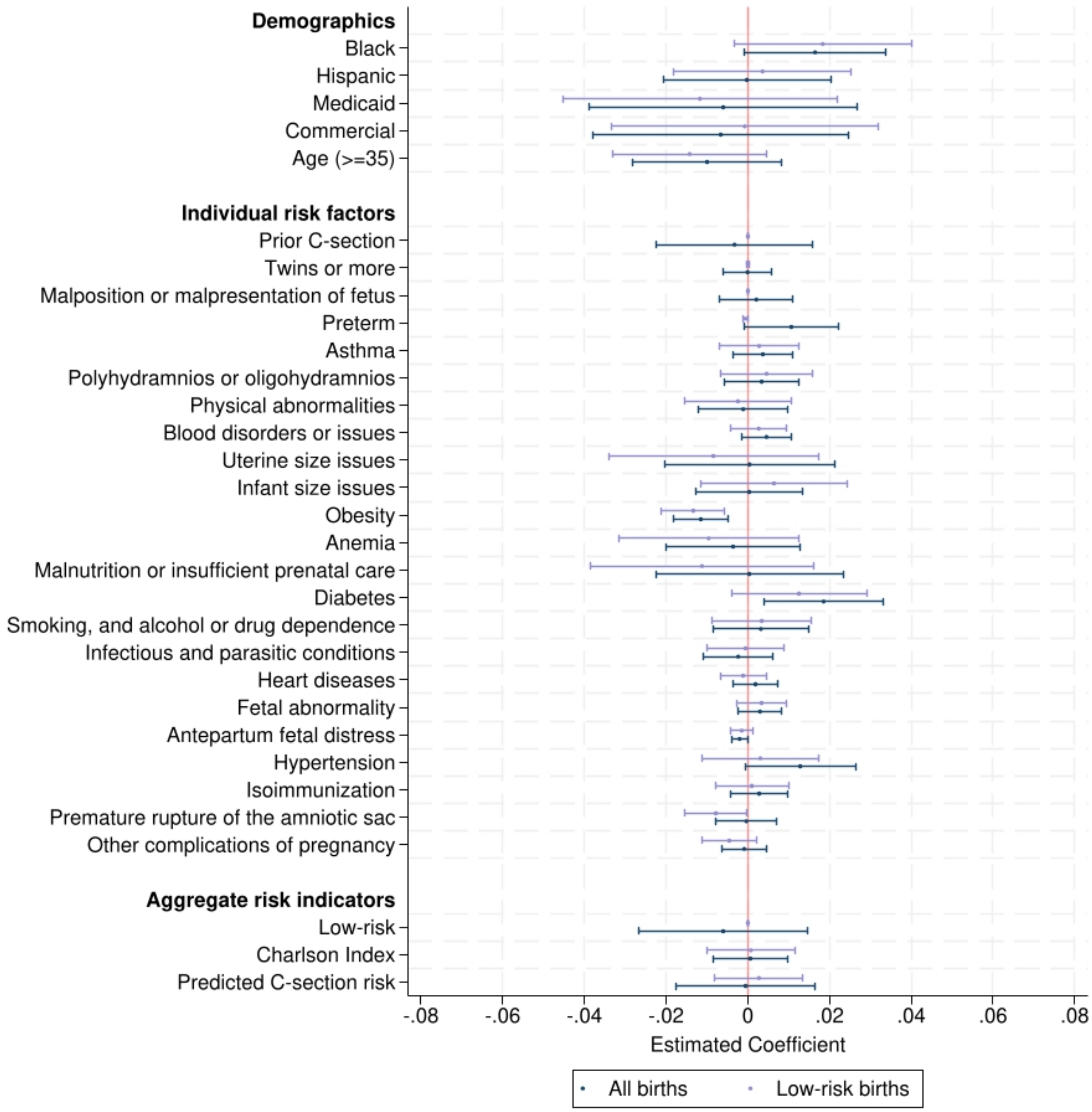

*Notes:* This figure shows C-section rates in the U.S. and Florida from 2004 to 2009. National rates are sourced from the CDC's Natality Database (see https://wonder.cdc.gov/natality.html for details). Florida rates are calculated using hospital inpatient data from the Florida Agency for Health Care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

**Figure 2. Distribution of Physician Housing Returns**



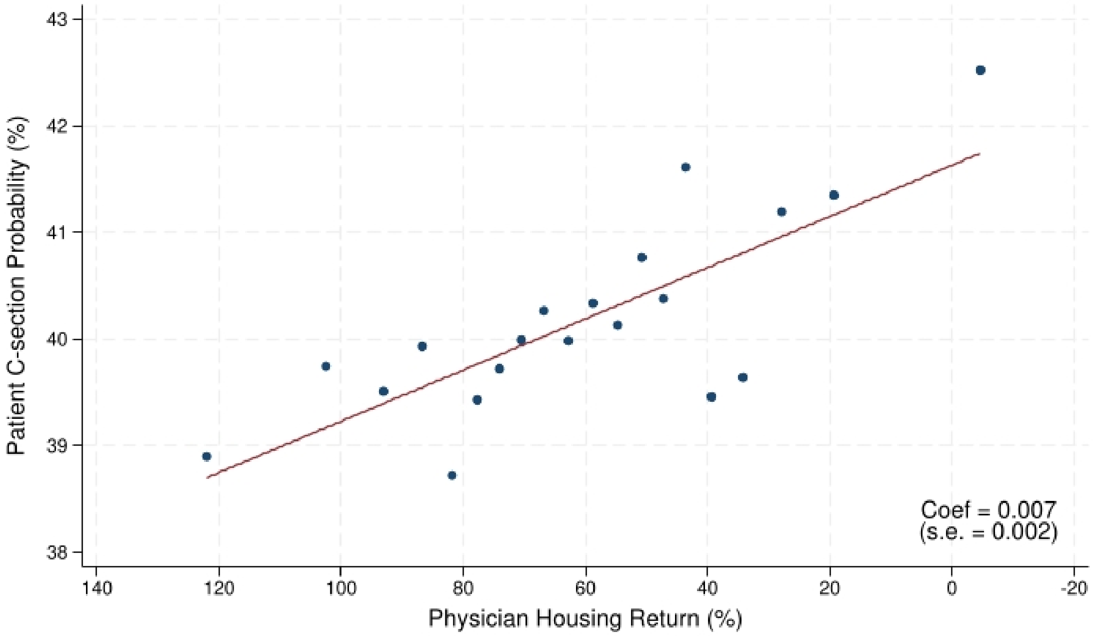

*Notes:* This boxplot shows the distribution of housing returns among physicians for each quarter from 2004 to 2009. Physician homeowners are identified using CoreLogic data. Housing returns are calculated as cumulative returns since the time of purchase, based on the Zillow Home Value Index, and are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

**Figure 3. Balance Test**




*Notes:* This figure presents the results of the balance test, as described in Section III.C. Each point represents a coefficient estimate from a separate regression of the row variable on physician housing returns (reversed in sign), with 95% confidence intervals shown. The row variables include patient demographics, individual risk factors, and aggregate risk indicators. Housing returns are calculated as cumulative returns since the time of purchase. All regressions include physician, hospital×year-quarter, and patient zip code×year-quarter fixed effects. The test is performed on both the full sample of all births and a subsample of low-risk births. Both samples cover the period from 2007 to 2009.

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




*Notes:* This binscatter plot provides model-free evidence on the relationship between C-section rates and physician housing returns using data from 2007 to 2009. Patients are grouped into 10 equal-sized bins based on their physicians' cumulative housing returns since purchase (expressed in percentage points), shown on the horizontal axis. For each bin, the average probability of C-section is plotted on the vertical axis. Both C-section probabilities and housing returns are residualized on physician fixed effects. The red solid line represents a linear fit estimated over the binned averages, with the slope coefficient being 0.007 (s.e.=0.002).

## Table 1. Summary Statistics

| *Sample* | *Unmatched physicians* Mean | SD | *Matched physicians* Mean | SD |
|---|---|---|---|---|
| ***Panel A: Patient-level variables*** | | | | |
| **Individual characteristics** | | | | |
| Age | 27.759 | [5.997] | 27.983 | [5.975] |
| Black | 0.195 | [0.396] | 0.212 | [0.409] |
| Hispanic | 0.217 | [0.412] | 0.193 | [0.394] |
| Medicaid | 0.495 | [0.500] | 0.444 | [0.497] |
| Commercial | 0.420 | [0.494] | 0.476 | [0.499] |
| Weekend delivery | 0.171 | [0.376] | 0.171 | [0.377] |
| **Individual risk factors** | | | | |
| Prior C-section | 0.200 | [0.400] | 0.194 | [0.395] |
| Malposition or malpresentation of fetus | 0.046 | [0.209] | 0.046 | [0.210] |
| 35 years of age or older | 0.154 | [0.361] | 0.159 | [0.366] |
| Twins or more | 0.016 | [0.125] | 0.017 | [0.128] |
| Preterm | 0.066 | [0.248] | 0.068 | [0.252] |
| Asthma | 0.027 | [0.161] | 0.026 | [0.160] |
| Polyhydramnios or oligohydramnios | 0.034 | [0.180] | 0.035 | [0.183] |
| Physical abnormalities | 0.059 | [0.235] | 0.059 | [0.236] |
| Blood disorders or issues | 0.021 | [0.143] | 0.022 | [0.147] |
| Uterine size issues | 0.227 | [0.419] | 0.229 | [0.420] |
| Infant size issues | 0.055 | [0.228] | 0.060 | [0.237] |
| Obesity | 0.024 | [0.153] | 0.025 | [0.155] |
| Anemia | 0.083 | [0.276] | 0.085 | [0.278] |
| Malnutrition or insufficient prenatal care | 0.245 | [0.430] | 0.247 | [0.431] |
| Diabetes | 0.061 | [0.239] | 0.062 | [0.242] |
| Smoking, and alcohol or drug dependence | 0.071 | [0.257] | 0.071 | [0.257] |
| Infectious and parasitic conditions | 0.030 | [0.170] | 0.031 | [0.172] |
| Heart diseases | 0.010 | [0.099] | 0.010 | [0.102] |
| Fetal abnormality | 0.013 | [0.112] | 0.013 | [0.115] |
| Antepartum fetal distress | 0.003 | [0.055] | 0.003 | [0.059] |
| Hypertension | 0.082 | [0.275] | 0.084 | [0.277] |
| Isoimmunization | 0.022 | [0.147] | 0.025 | [0.155] |
| Premature rupture of the amniotic sac | 0.031 | [0.174] | 0.031 | [0.173] |
| Other complications of pregnancy | 0.017 | [0.128] | 0.016 | [0.127] |
| **Aggregate risk indicators** | | | | |
| Low-risk | 0.708 | [0.455] | 0.711 | [0.453] |
| Charlson Index | 0.031 | [0.207] | 0.030 | [0.202] |
| Predicted C-section risk | 0.406 | [0.334] | 0.405 | [0.332] |
| **Treatment** | | | | |
| C-section rate (%) | 41.055 | [49.194] | 40.179 | [49.026] |
| Unscheduled C-section rate (%) | 9.433 | [29.228] | 9.228 | [28.941] |
| Observations | 143853 | | 187873 | |
| ***Panel B: Physician-level variables*** | | | | |
| Female | 0.636 | [0.482] | 0.593 | [0.492] |
| Tenure (as of 2006) | 18.837 | [9.811] | 17.868 | [8.951] |
| Number of deliveries per quarter | 31.249 | [22.278] | 30.446 | [20.807] |
| C-section rate (%) | 41.896 | [12.697] | 41.492 | [11.895] |
| Number of houses (as of 2006/12/31) | | | 1.345 | [0.603] |
| Occupancy (in years, as of 2006/12/31) | | | 4.746 | [4.341] |
| Purchase price of houses (in 2006 dollar) | | | 544212.383 | [389646.778] |
| Observations | 368 | | 484 | |

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

## Table 2. Effects on Treatment Choices

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

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

*Notes:* This table reports baseline results from patient-level regressions of C-section indicators on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. Columns (1)–(3) indicate for any C-section, whereas Column (4) and (5) indicate for unscheduled and scheduled C-sections, respectively. All columns control for physician fixed effects and patient characteristics, including demographics, insurance type, weekend delivery, and clinical risk factors based on comorbidities observed prior to labor onset. Columns (2)–(5) additionally include hospital$\times$year-quarter fixed effects. Columns (3)–(5) additionally include patient zip code$\times$year-quarter fixed effects. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are shown in parentheses.

**Table 3. Heterogeneous Effects by Physician Characteristics**

***Panel A: All patients***

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

***Panel B: Low-risk patients***

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

*Notes:* This table reports results from subsample regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Columns (1)–(2) split the sample by physicians' ex ante excessive C-section rates; Columns (3)–(4) by local physician density; and Columns (5)–(6) by physician gender. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

**Table 4. Heterogeneous Effects by Patient Characteristics**

***Panel A: All patients***

| | *Patient race and ethnicity* | | | *Appropriateness of C-section* | | |
|---|---|---|---|---|---|---|
| | (1) NH Black | (2) Hispanic | (3) Others | (4) Low | (5) Medium | (6) High |
| Physician housing return | 6.894 | 1.193 | 1.318 | 2.163 | 5.516 | 1.574 |
| | (2.124) | (1.498) | (1.324) | (1.563) | (2.121) | (1.443) |
| Patient covariates | X | X | X | X | X | X |
| Physician FE | X | X | X | X | X | X |
| Hospital-year-quarter FE | X | X | X | X | X | X |
| Patient zip code-year-quarter FE | X | X | X | X | X | X |
| Mean (dep. var.) | 39.18 | 44.33 | 39.27 | 13.87 | 25.19 | 83.83 |
| Observations | 39,860 | 36,201 | 111,812 | 75,272 | 50,052 | 62,549 |

***Panel B: Low-risk patients***

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

*Notes:* This table reports results from subsample regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Columns (1)–(3) split the sample by patients' race and ethnicity; Columns (4)–(6) by patients' medical appropriateness of receiving a C-section. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

**Table 5.** **Effects on Maternal Health Outcomes**

***Panel A: All patients***

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

***Panel B: Low-risk patients***

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

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

## Table 6. The Mechanism of Financial Distress

***Panel A: All patients***

| | *Positive shocks (2004–2006)* | | | *Physicians with high LTV* | | |
|---|---|---|---|---|---|---|
| | (1) C-section | (2) Unscheduled C-section | (3) Scheduled C-section | (4) C-section | (5) Unscheduled C-section | (6) Scheduled C-section |
| Physician housing return | 0.697 | 0.385 | 0.312 | 8.428 | 7.008 | 1.420 |
| | (1.075) | (0.808) | (0.900) | (3.946) | (3.665) | (3.997) |
| Patient covariates | X | X | X | X | X | X |
| Physician FE | X | X | X | X | X | X |
| Hospital-year-quarter FE | X | X | X | X | X | X |
| Patient zip code-year-quarter FE | X | X | X | X | X | X |
| Mean (dep. var.) | 37.55 | 9.32 | 28.24 | 41.26 | 9.36 | 31.90 |
| Observations | 193,784 | 193,784 | 193,784 | 50,139 | 50,139 | 50,139 |

***Panel B: Low-risk patients***

| | *Positive shocks (2004–2006)* | | | *Physicians with high LTV* | | |
|---|---|---|---|---|---|---|
| | (1) C-section | (2) Unscheduled C-section | (3) Scheduled C-section | (4) C-section | (5) Unscheduled C-section | (6) Scheduled C-section |
| Physician housing return | 0.731 | 0.198 | 0.533 | 13.488 | 8.819 | 4.669 |
| | (1.300) | (0.985) | (1.010) | (5.622) | (4.860) | (4.382) |
| Patient covariates | X | X | X | X | X | X |
| Physician FE | X | X | X | X | X | X |
| Hospital-year-quarter FE | X | X | X | X | X | X |
| Patient zip code-year-quarter FE | X | X | X | X | X | X |
| Mean (dep. var.) | 21.48 | 10.90 | 10.57 | 23.56 | 11.44 | 12.12 |
| Observations | 141,533 | 141,533 | 141,533 | 35,413 | 35,413 | 35,413 |

*Notes:* This table reports results from patient-level regressions of C-section indicators on physician housing returns, estimated using a linear probability model as specified in Equation (2). Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. Columns (1)–(3) cover the sample period of 2004–2006. Columns (4)–(6)'s sample spans 2007–2009 as in the main analytic sample but only include physicians with Loan-To-Value (LTV) ratios higher than 90%. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

**Table 7. Effects on Other Treatment Margins**

| *Panel A: All patients* | *Induction* | *Vacuum/Forceps* | *Hosp. charges* | *# Deliveries* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Physician housing return | -0.711 | 0.907 | 0.021 | -0.042 |
| | (0.848) | (0.509) | (0.009) | (0.060) |
| Year-quarter FE | | | | X |
| Physician FE | X | X | X | X |
| Patient covariates | X | X | X | |
| Hospital-year-quarter FE | X | X | X | |
| Patient zip code-year-quarter FE | X | X | X | |
| Mean (dep. var.) | 16.63 | 5.22 | 9.35 | 41.51 |
| Observations | 187,873 | 187,873 | 187,873 | 5,678 |

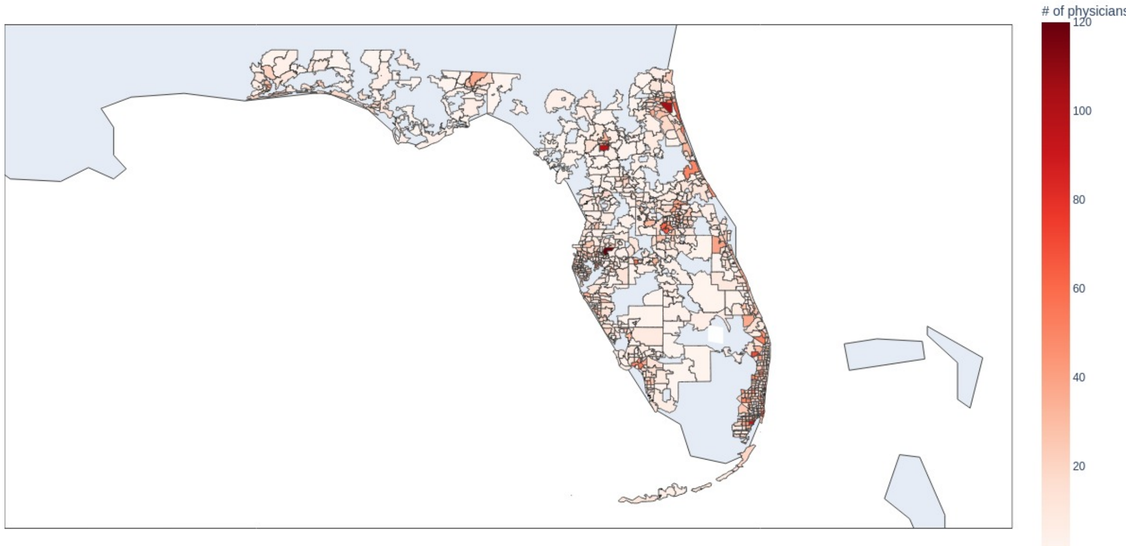
| *Panel B: Low-risk patients* | *Induction* | *Vacuum/Forceps* | *Hosp. charges* | *# Deliveries* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Physician housing return | -1.369 | 0.918 | 0.021 | -0.045 |
| | (1.126) | (0.559) | (0.010) | (0.060) |
| Year-quarter FE | | | | X |
| Physician FE | X | X | X | X |
| Patient covariates | X | X | X | |
| Hospital-year-quarter FE | X | X | X | |
| Patient zip code-year-quarter FE | X | X | X | |
| Mean (dep. var.) | 22.15 | 5.62 | 9.26 | 41.78 |
| Observations | 133,551 | 133,551 | 133,551 | 5,637 |

*Notes:* This table reports results from regressions of other treatment margins on physician housing returns. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1) and (2) use indicators (scaled by 100) for labor induction and vacuum/forceps use, respectively. Column (3) uses logged hospital charges as the outcome. Columns (1)–(3) include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Column (4) presents results from a Poisson regression of physician-level delivery counts, controlling for year-quarter and physician fixed effects. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

# Online Appendix

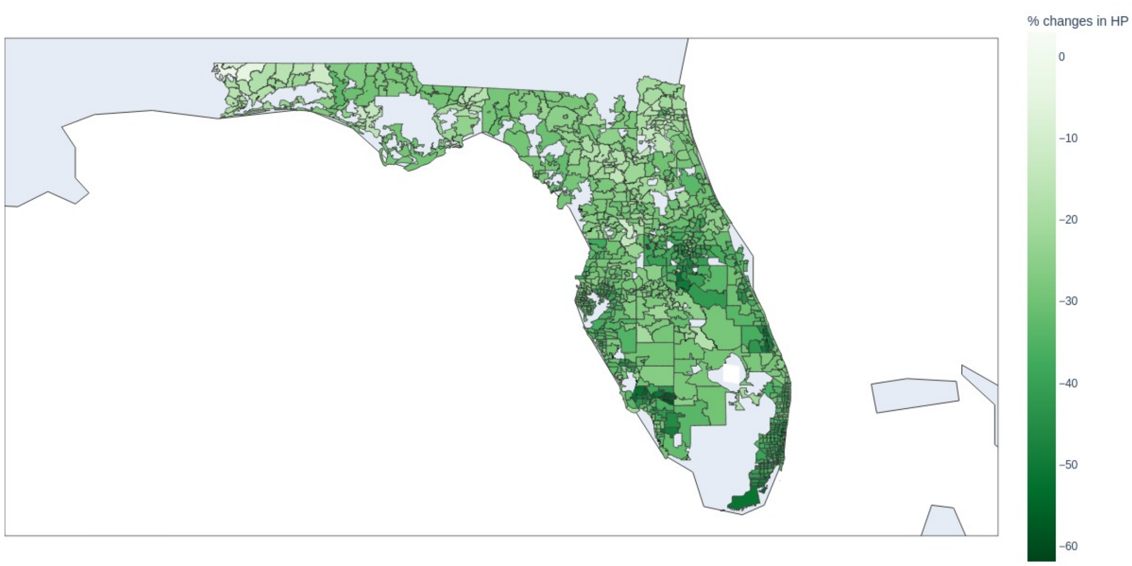
## A Additional Figures and Tables

**Figure A1. Number of Physicians in Each Zip Code**



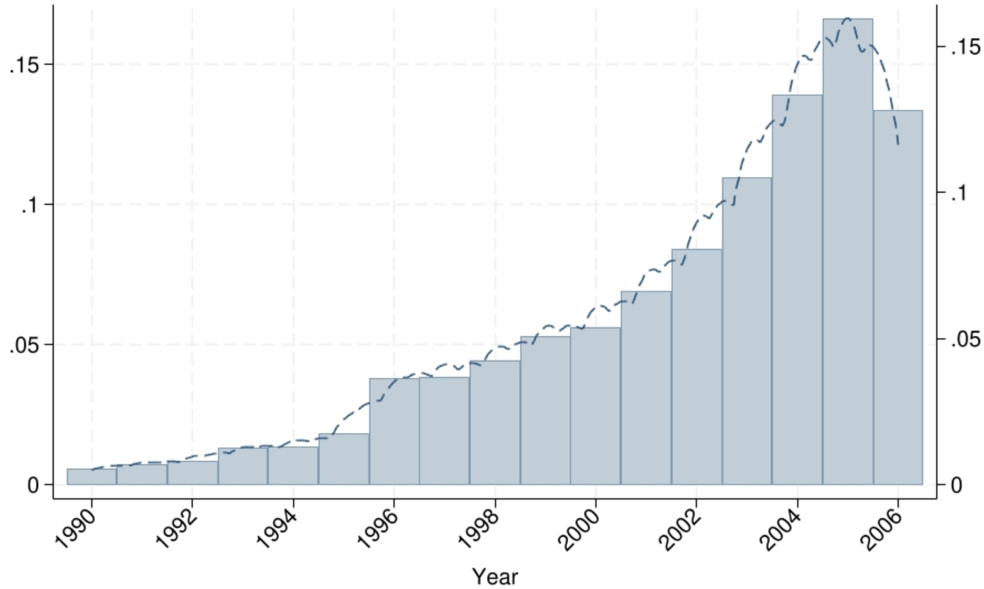

*Notes:* This figure shows the number of physicians residing in each Florida zip code. Physicians' residences are identified following the procedures described in Appendix B. Only houses held at the end of 2006 are included (i.e., excluding houses sold before 2006 or purchased after 2007). Zip codes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

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



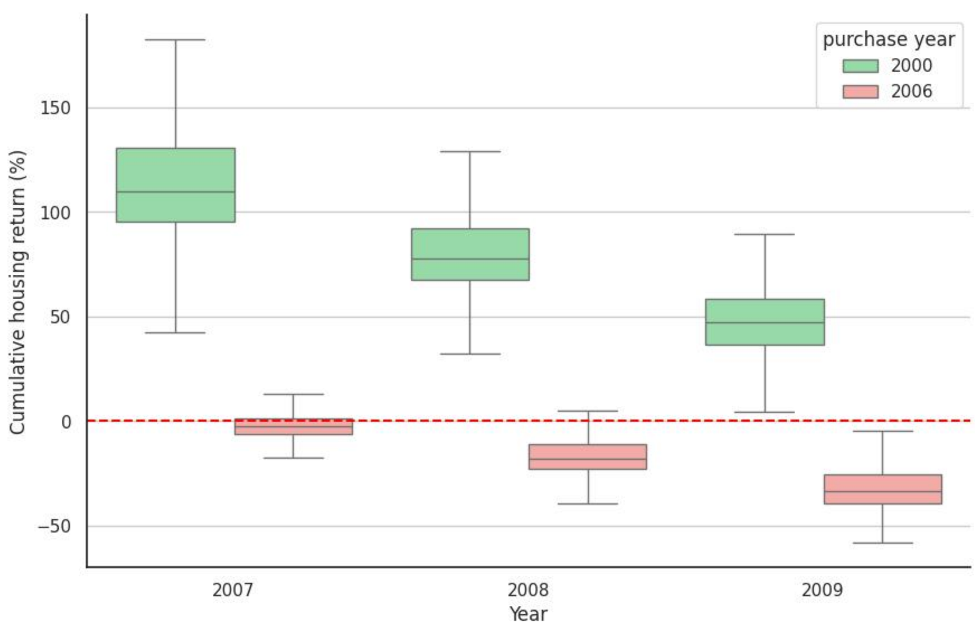

*Notes:* This figure displays the percentage change in the Zillow Home Value Index (ZHVI) for each Florida zip code from 2007 to 2009. Zip codes with missing ZHVI data are excluded.

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




*Notes:* This histogram shows the fraction of physicians who purchased houses each year. Physicians' residences are identified as described in Appendix B. The sample excludes purchases before 1990 or after 2006. The dashed line represents the kernel density estimate.

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




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

## Table A1. Nonlinear Probability Model

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

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

## Table A2. Alternative Clustering of Standard Errors

***Panel A: All patients***

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

***Panel B: Low-risk patients***

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

*Note:* This table reports results from patient-level regressions of C-section indicators on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. Columns (1)–(3) cluster standard errors at the hospital level; Columns (4)–(6) at the patient zip code level; Columns (7)–(9) at the physician zip code level. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

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

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

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

*Notes:* This table presents results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since the time of purchase and are reversed in sign. The C-section indicator is scaled by 100. Column (1) restricts the sample to patients whose residential zip code is within 10 miles of their hospital's zip code. Column (2) adds patient zip code×year-quarter fixed effects. Column (3) restricts the sample to patients whose 3-digit zip code differs from that of their physician. Column (4) further includes patient zip code×physician fixed effects. Column (5) limits the sample to physicians practicing at a single hospital during the sample period. Column (6) adds physician×hospital fixed effects. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panel A reports results for all patients; Panel B restricts the sample to low-risk patients. Standard errors, clustered at the physician level, are reported in parentheses.

## Table A4. Alternative Measures of Real Estate Shocks

***Panel A: All patients***

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

***Panel B: Low-risk patients***

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

*Notes:* This table presents results from patient-level regressions of the C-section indicator (scaled by 100), estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Columns (1)–(3) use alternative measures of physician housing shocks: Column (1) uses the cumulative return lagged one quarter; Column (2) uses the return over the most recent quarter; and Column (3) uses the return over the past year. All return measures are reversed in sign. Column (4) uses the (logged) level of house prices, computed as the inflation-adjusted purchase price multiplied by the cumulative housing return. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panel A reports results for all patients; Panel B restricts the sample to low-risk patients. Standard errors, clustered at the physician level, are reported in parentheses.

## Table A5. Alternative Sample Specifications

**_Panel A: All patients_**

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

**_Panel B: Low-risk patients_**

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

*Notes:* This table reports results from patient-level regressions of C-section indicators on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. Columns (1)–(3) include physicians who entered the labor force after the recession began (i.e., late entries) as well as those who retired before the recession ended (i.e., early exits). Columns (4)–(6) allow physicians' house holdings to be time-varying and track physician housing returns over time. All regressions include physician fixed effects, hospital×year-quarter fixed effects, patient zip code×year-quarter fixed effects, and patient covariates, including demographics, insurance type, weekend delivery, and clinical risk factors. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are reported in parentheses.

## B Sample Construction

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

For these discharges, 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.[1] NPIs enable linkage to the National Provider Identifier (NPI) registry of the National Plan and Provider Enumeration System (NPPES).[2] About 96–99% of physicians can be matched to either the licensee profiles or the NPPES registry.

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

I follow La Forgia (2022)'s program for coding maternal risk factors using ICD codes that indicate risks present at the time of admission.[3] For maternal morbidity, I follow the methodologies of Johnson and Rehavi (2016), Freedman and Hammarlund (2019), La Forgia (2022), Callaghan et al. (2012), Kilpatrick et al. (2016), and CDC, using ICD codes to identify complications *not* present at the time of admission.[4]. Appendix Table B1 summarizes the codes used for maternal morbidity.

**Table B1. ICD Codes for Maternal Morbidity**

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

[1] https://mqa-internet.doh.state.fl.us/downloadnet/Profile.aspx

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

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

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

**Physician House Holdings.** I begin with all ownership transfer records and mortgage records from CoreLogic. I 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 (CLIP), property location zip code, transaction date, and sales amount. I then collapse the transaction-level data to the doctor×house×date level. To achieve this, I first collapse the data to the doctor×house×date×role level. For example, if a physician appears in multiple "BUYER X" fields, I keep only the "BUYER" role. For each house, I keep the earliest purchase record and the latest sale record.

Next, I calculate the number of transaction records associated with each physician×house pair. I drop physicians with more than two transaction records for the same house, as these are likely duplicate entries for the same transaction. As a result, there are four possible transaction types for each physician×house pair. (1) Sell-first-then-buy: These pairs are dropped. (2) Buy-first-then-sell: These pairs are retained. (3) Buy-only: These pairs are retained. (4) Sell-only: For these records, I assign a pseudo purchase year based on the median purchase year within the same 5-digit zip code. For zip codes without sufficient data, I assign the median purchase year at the state level (i.e., 2005). These pairs are then reclassified as "buy-first-then-sell" and retained.

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

**House Price Index.** The Zillow House Value Index (ZHVI) is only available starting from the year 2000. 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: $HPI_t^{\text{ZHVI}} = \gamma \cdot HPI_t^{\text{FHFA}}, \forall t < 2000$. Appendix Figure B1 below shows the *average* imputed ZHVI values.

**Figure B1. Imputing ZHVI Using FHFA Price Index**