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

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July 7, 2025

Abstract

This paper examines how physicians' financial health influences their treatment decisions and patient outcomes. I leverage a novel data set that links physicians' real estate portfolios to patient hospitalization records, and exploit within-physician variation in housing returns for identification. In the context of childbirth where physicians face financial incentives to adopt C-sections over vaginal deliveries, I find that a one-standard-deviation decline in physician housing returns increases C-section rates by 1.6 percentage points, or 4%. However, there is no evidence that maternal health outcomes are substantially affected. Finally, I show that physicians' responses are primarily driven by financial distress.

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

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

I Introduction

Spending on physician services is substantial and growing in developed countries (Martin et al., 2025). In the U.S., National Health Expenditure (NHE) on physician and clinical services increased by 7.4 percent and reached 978 billion dollars in 2023, accounting for about 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; 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 various financial shocks. As some of the highest earners in the country (Gottlieb et al., 2025), physicians often hold a considerable portion of their wealth in assets such as stocks and real estate. Volatile returns on these assets can expose them to unpredictable wealth losses and even create financial distress.[1] In addition, physicians, especially those early in their careers, often carry nontrivial personal debts, including student loans and mortgages. As a result, the health of their balance sheets can be particularly sensitive to shocks such as interest rate changes and shifts in student loan policies. For example, the One Big Beautiful Bill Act caps federal student loans for medical students at \$200,000—–roughly the median level of education debt but still below the median cost of attending four years of medical school (Association of American Medical Colleges, 2020)—–raising concerns about its implications for physicians' personal finance.

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

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

various risk profiles. To explicitly tackle this issue, I link the 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 high-stakes clinical setting, labor and delivery, or childbirth, which has several advantages for my purpose. First, the major treatment margin is well-defined in this inpatient setting—vaginal delivery versus cesarean section (C-section). Physicians in this context (i.e., obstetricians and gynecologists, or OB-GYNs) have 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).[2] I therefore hypothesize that physicians in worse financial conditions are more tempted to perform C-sections, all else equal.

For the empirical analysis, I construct a time-varying, physician-level measure of cumulative housing returns, calculated as the change in average house values in the physician's zip code since the time of purchase. Existing studies in household finance have used the same 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 quasi-experimental variation in housing returns, which is mainly driven by more aggregate house price movement over the business cycle, after conditional on physician fixed effects (i.e., pre-determined individual housing portfolios).

Importantly, the physician fixed effects are useful in controlling for time-invariant confounds at the physician level such as risk preferences and surgical skills. To further alleviate concerns of endogeneity, I also augment the baseline specification with two additional sets of fixed effects. First, hospitals can be subject to contemporaneous financial shocks and have incentives to influence medical treatments (Dranove et al., 2017; Adelino et al., 2022). I therefore include hospital$\times$time fixed effects to account for potentially parallel responses at the hospital level. Second, 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; Schwandt, 2018). To rule out such a demand-side channel, I further control for patient zip code$\times$time fixed effects in the regression.

As the main result, I find that a one-standard-deviation decrease in physicians' housing returns leads to 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 more 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. These results are economically meaningful and equivalent to the effect of lowering the physician fee differential between C-sections and vaginal deliveries by

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

about \$250 (Gruber et al., 1999; Alexander, 2017; Foo et al., 2017), or that of increasing the OB-GYN density by about 26% (Gruber and Owings, 1996).

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

One might wonder if the higher C-section rate is a result of physicians using less assisted methods when attempting vaginal deliveries. I consider two examples of such methods—induction and ancillary procedures (i.e., vacuum and forceps). There is no evidence for less use of induction in the first stage of labor, and if anything, slightly more use of ancillary procedures in the second stage of labor. One might also wonder if physicians increase the overall treatment intensity during the hospital stay. I find that there is indeed an increase, as proxied by hospital charges, but such an increase is mostly explained by the difference between C-sections and vaginal deliveries. Lastly, I show that physicians do not appear to deliver more babies in response to negative financial shocks (i.e., the extensive margin).

A natural follow-up question is whether the increase in use of C-section 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 explore the potential mechanisms through which financial shocks alter physicians' treatment choices. On the one hand, physicians' marginal utility of income can increase as their housing wealth decreases, motivating them to adopt the more lucrative procedure (i.e. C-section)—this is the typical wealth effect. On the other hand, declining house equity and tighter liquidity constraint can limit physicians' financial capabilities and create financial distress. Physicians may be even more desired of recouping wealth losses and avoiding further costs from for example loan default, house foreclosure, or even personal bankruptcy. I explain these two mechanisms in a discrete-choice framework of treatment choices in childbirth, which incorporates two important motives behind physicians' decisions: financial incentives and patient welfare.

Evidence supports physician financial distress as the primary mechanism underlying the higher C-section rate. First, positive wealth shocks should trigger the wealth effect but not financial distress. One should therefore expect physicians' responses even when house values are rising if the wealth effect plays role. However, I find null results in years leading up to the crisis (2004–2006) and when the real estate market started to recover (2013–2015). Second, if financial distress is driving physicians' responses, the effect should be more pronounced when the liquidity constraint is tighter. Consistent with this prediction, I find that the results are statistically and economically more significant for physicians under greater liquidity constraints, as proxied by high Loan-To-Value (LTV) ratios.

This paper speaks to several areas of research. First, it contributes to a burgeoning literature on how provider financial health 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.[3] 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$\times$time fixed effects, helping to isolate physicians' responses from contemporaneous responses at the facility level.

More broadly, this paper adds to the literature on real effects of household 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

[3] 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.

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.

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 approximately 4 million newborns each year, accounting for 11% of all hospital stays and 4% of all inpatient hospital costs (Podulka et al., 2011). The primary treatment choice in childbirth is between vaginal delivery and cesarean section (C-section). Among all newborns in the U.S. nowadays, approximately one-third are delivered via C-section. 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).

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 diagnosing conditions that justify a C-section.

Cesarean procedures can be life-saving for certain patients, especially for those with severe medical conditions. They can also save infants from the uncertainties of prolonged and difficult labor. On the other hand, although rarely leading to maternal mortality, C-sections may result in maternal morbidity, including complications such as infection, hemorrhage, and blood clots during and after delivery. Due to their invasive nature, C-sections often require a longer hospital stay (2–4 days compared to 1–2 days for vaginal deliveries) and 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.[4] 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).[5] While C-sections are more financially rewarding, they are not necessarily more labor-intensive. Vaginal deliveries often involve greater uncertainty in waiting time and require continuous monitoring during labor, which may last several hours. In contrast, C-sections typically take only 45–60 minutes, reducing opportunity costs and offering "convenience" to physicians (Keeler and Brodie, 1993).

Failure to perform a timely C-section is a common allegation in malpractice suits and can result

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

[5] 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.

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

Taken together, the clinical setting of childbirth is particularly useful as physician discretion likely plays a significant role in deciding which medical treatment a patient should receive. C-sections appear to be more financially rewarding for physicians than vaginal deliveries. 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 type, as well as diagnoses and procedures via ICD-9 codes. The data also allows me to observe a series of patient outcomes, such as length of stay, discharge status, and hospital charges. I begin by extracting hospital inpatient records related to childbirth, and restrict the sample to patients aged 18 to 50, with a length of stay of no more than seven days, a Florida residence, and non-missing demographic information. For example, between the first quarter of 2007 and the fourth quarter of 2009, the dataset identifies 560,855 childbirths, approximately 40% of which were delivered via C-section.

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

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

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

In the main analysis, I restrict the sample period to the onset of the Great Recession (2007–2009), when house values declined most significantly. As an additional analysis to test whether the effects are symmetric, I also examine the preceding period (2004–2006) during which house prices rose almost universally and the recovery period (2013–2015) when house prices started to increase again. Table 1 presents descriptive statistics for both the analytical sample of matched physicians and the leave-out sample of unmatched physicians. The matching procedures and filters described above identify 484 matched physicians who collectively delivered 187,873 births from 2007 to 2009.[6] Panel A of Table 1 shows that matched and unmatched physicians are fairly similar in terms of the patients they attend, regardless of patient characteristics, individual risk factors, or aggregate risk.

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

[6] There are 368 unmatched physicians in the inpatient data. The resulting match rate is 57%, comparable to that in Bernstein et al. (2021), which uses a similar method to identify the residences of patent applicants.

III.B Measuring Financial Shocks to Physicians

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

Because CoreLogic does not document a property's market value after purchase unless it is resold—–and such repeat sales are rare in the data—–I proxy subsequent home values using the Zillow Home Value Index (ZHVI) for zip code z at time t, denoted $ZHVI_{z,t}$.[7] When a physician owns multiple homes, I compute a weighted average cumulative housing return, as shown in Equation (1) below.

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

Here, $\mathbf{Z}_j$ represents the set of zip codes where physician j's houses are located. To avoid complications from strategic investment or divestment by physicians after the crisis began, I fix each physician's housing portfolio $\mathbf{Z}_j$ as of the end of 2006 and assume they hold it through the end of 2009 in the main analysis.[8] The weight w_z reflects the share of the house in zip code z in the physician's portfolio, calculated based on its inflation-adjusted purchase price.

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

Compared to other market-level indicators of house price movements, $R_{j,t}$ is less likely to be confounded by unobserved factors that simultaneously influence patient demand, as it incorporates two physician-specific sources of heterogeneity. The first stems from the zip code(s) where physician j resides, $\mathbf{Z}_j$. Physicians' homes are scattered across many zip codes. Appendix Figure A1 maps the number of physicians residing in each Florida zip code. These areas exhibit heterogeneous price trends, even within the same recession period (Bogin et al., 2019). Appendix Figure

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

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

A2 illustrates the variation in ZHVI percentage changes across zip codes during 2007–2009. The second source of heterogeneity comes from the timing of house purchases, t_0. Appendix Figure A3 shows the distribution of purchase years, which has a long left tail and over half of the physicians becoming homeowners after 2000. This variation means that even physicians living in the same zip code can experience different housing returns, depending on their purchase timing. Appendix Figure A4 highlights this variation by showing the distribution of simulated cumulative returns for physicians living in different zip codes, assuming home purchases in 2000 versus 2006.

Combining these two dimensions of physician-level heterogeneity, $R_{j,t}$ offers useful variation for identification, which I elaborate on later alongside the econometric specification. Figure 2 summarizes the distribution of $R_{j,t}$ across physicians and over time. For the average physician, cumulative housing return reached almost 100% by the last quarter of 2006, indicating that house values had nearly doubled relative to purchase prices. However, there was considerable variation across physicians: at the same point in time, physicians at the 25th and 75th percentiles had cumulative returns of 40% and 148%, respectively. Most of these gains were wiped out by the end of 2009. By then, the average physician held just a 20% cumulative return, underscoring the severity of the recession-induced decline in housing wealth and the magnitude of the financial shocks analyzed in this study.

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

This baseline specification controls for a comprehensive set of patient characteristics, $\mathbf{X}_i$, including demographics (e.g., race and ethnicity), insurance type (e.g., Medicaid or commercial), weekend delivery status, and 24 clinical risk factors observed before labor onset (e.g., prior C-section, advanced maternal age). These risk factors help adjust for the medical appropriateness of C-sections, ensuring that the analysis compares treatment choices among clinically similar patients. Summary statistics for these covariates are reported in Table 1.[9]

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

Finally, I include two additional sets of fixed effects to address potential endogeneity concerns. The first relates to a parallel supply-side channel. Specifically, prior research has documented substantial variation in C-section rates across hospitals (Kozhimannil et al., 2013; Card et al., 2023; Robinson et al., 2024), and found that hospital practices are sensitive to financial shocks (Dranove et al., 2017; Adelino et al., 2022). If physicians who experience larger wealth shocks disproportionately work in hospitals with systematically higher or lower C-section rates—–or are influenced by hospital-level incentives—–the estimate of β may be biased. To address this, I include hospital×year-quarter fixed effects, $\delta_{h,t}$, in Equation (2), which helps to isolate supply-side responses at the individual physician level from those at the facility level.

The second concern arises from confounding demand shocks. For instance, existing research has shown that wealth or income shocks can affect households' healthcare utilization and spending (Acemoglu et al., 2013; Tran et al., 2023), and can even impact physical and mental health (McInerney et al., 2013; Schwandt, 2018). If physicians who are exposed to greater financial shocks tend to treat patients from recession-affected zip codes—–where health conditions may have worsened—–the estimated effect on physician behavior could be biased upwards. To alleviate this concern, I leverage the availability of patients' residential zip codes in the inpatient data and include patient zip code×year-quarter fixed effects, $\phi_{c,t}$, in Equation (2). This helps to absorb latent demand-side factors to a good extent, even if such unobservables are time-varying.

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

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

risk—yield similar results. These findings suggest that patient characteristics are conditionally balanced across physicians exposed to different levels of housing return, lending credibility to the conditional independence assumption.

The identification also requires that, conditional on patient covariates and the fixed effects, other unobserved physician characteristics that may affect patient treatments are mean independent of physician housing return (i.e., the exclusion restriction). While this assumption is difficult to test directly, it appears plausible for several reasons. First, by construction, physicians' housing portfolios are fixed prior to the onset of the Great Recession and are therefore unlikely to be correlated with factors that influence their treatment behavior ex post. Although one might worry that physicians could have anticipated the housing crisis and made strategic investment or divestment, prior studies such as Cheng et al. (2014) have shown that even financial professionals failed to foresee the housing bust, let alone medical students and physicians, who are reportedly less financially literate (Jayakumar et al., 2017; Igu et al., 2022). Second, physician fixed effects have accounted for differences in housing returns that is determined by the choice of location and timing of home purchases. The remaining within-physician variation is primarily driven by house price movements at more aggregate levels, and can be thought of as good as that from randomly exposing physicians to different extents of financial shocks in a quasi-experiment. Lastly, the inclusion of physician fixed effects alongside year-quarter fixed effects (through $\delta_{h,t}$ and $\phi_{c,t}$) implicitly absorbs time-varying physician characteristics that evolve linearly over time, such as age or years of work experience, even if they are not explicitly included in the model. Admittedly, the aforementioned controls cannot fully eliminate all sources of endogeneity. However, any remaining threats to identification would need to be correlated with physician housing returns in a time-varying manner.

For the main analysis, I estimate Equation (2) using a linear probability model to allow inclusion of high-dimensional fixed effects and more straightforward interpretation of the coefficients. That said, Appendix Table A1 confirms that results are robust to alternative non-linear models such as Logit. Unless otherwise noted, I cluster standard errors at the physician level for most regressions. Appendix Table A4 reports similar results when standard errors are clustered at more conservative levels, including hospital, patient zip code, and physician zip code.

IV Results

This Section provides the empirical results. I start by estimating the effect of physicians' financial health on the main treatment margin—vaginal delivery versus C-section—in subsection IV.A. 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.E. Lastly, I report a battery of robustness checks in subsection IV.F.

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 β 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$\times$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 tend to treat sicker 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$\times$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).

This effect is economically meaningful. Compared to related studies that use variation in physician fees between C-sections and vaginal deliveries (Gruber et al., 1999; Alexander, 2017; Foo et al., 2017), it is equivalent to the effect of lowering the physician fee differential by about \$240.[10] Gruber and Owings (1996) use the increase in physician density to proxy for negative income shocks. Based on their estimate, the effect in my paper is comparable to increasing the OB-GYN density by about 26%. My result is also in roughly the same magnitude of other estimates in the literature. For example, it is equivalent to about 65% of the gap in C-section rates between physician mothers and non-physician mothers (Johnson and Rehavi, 2016) and about 1.25 times the effect of OB-GYNs being acquired by physician practice management companies La Forgia (2022).

Finally, C-sections 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. 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.[11] 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 (≈ 0.65) leads to an increase of 2 percentage points in the low-risk C-section

[10]Specifically, using within-state over-time variation in Medicaid's pay differential between cesarean and vaginal deliveries (1988–1992), Gruber et al. (1999) estimate that a \$100 increase in the fee differential leads to a 0.7 percentage point rise in the C-section rate. Using a similar empirical strategy but more recent state-level Medicaid data (1990–2008), Alexander (2017) estimate that the C-section rate increases by 0.6 percentage points as the pay differential increases by \$100. Using data from private insurers in California, Foo et al. (2017) also estimate that a \$100 increase in the pay differential results in a 0.6 percentage point increase in the C-section rate. My estimate is therefore equivalent to the effect of lowering the pay differential by about $1.6/0.65 \times \$100 \approx \$250$.

[11]See AHRQ's Inpatient Quality Indicator 33 (IQI 33). 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.

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 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.[12] 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

[12] 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.

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.

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.[13] 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

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

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. 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 Other Treatment Margins

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

To begin with, one might wonder if the higher C-section rate is a result of physicians using less assisted methods when attempting vaginal deliveries. An example of such assisted methods is induction, which is used to stimulate uterine contraction and avoid a prolonged first stage of labor. Column (1) of Table 5 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 not appear to reduce necessary interventions early in the labor and delivery process. Another example of assisted methods is the use of vacuum devices and forceps, which are considered ancillary procedures and sometimes used in the second stage of labor. Column (2) of Table 5 uses an indicator for vacuum/forceps as the outcome and finds that patients are slightly more likely to receive these procedures when physician housing returns decrease. In fact, the increased use of vacuum/forceps is concentrated in vaginal births (see Appendix Table A2).

There could also be other treatments not captured by the use of C-sections, induction, or ancillary 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 5 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. This result, however, becomes insignificant once conditional on delivery mode, indicating that the increase in hospital charges is largely explained by the margin of C-section versus vaginal delivery (see Appendix Table A2).

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×year×quarter-level data set, controlling for physician and year×quarter fixed effects. The estimate from a Poisson model is reported in Column (4) of Table 5. The insignificant result is perhaps not surprising, as the number of baby deliveries can also be influenced by demand-side factors beyond physicians' control, such as fertility rates.

IV.E 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.[14] Column (1) of Table 6 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

[14] Poisson regressions using integer count data as the outcome produce similar results (see Appendix Table A3).

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 6 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 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 6. 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.[15]

As is shown in Columns (5) to (8) of Table 6, 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 6. Overall, I find no decisive evidence that physicians' responses to negative financial shocks substantially impact maternal health. If anything, higher C-section rates

[15] 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.

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.F Robustness

Results of several additional robustness checks are summarized in Appendix Tables A5 to A7. 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 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 A5 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 A5 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 A5 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 A5.

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 A5 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 A6 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 A6 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 A6, 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 A6 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 A7, 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 A7, 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, negative wealth shocks put physicians in financial distress, leading physicians to opt for C-sections to recoup lost wealth or avoid further costs. Understanding which 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 the finding of higher C-section rates documented in previous sections. This framework accounts for two important motives behind physicians' treatment choices: financial incentives and patient welfare. Next, in Section V.B, I provide additional evidence to distinguish the potential 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 two motives—personal earnings from physician fee (i.e., financial incentives) and medical benefits to the patient (i.e., physician altruism). Both 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.

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

The first component, $f_j(\omega_k)$, captures the pecuniary utility for physician j from providing treatment k, within which ω_k represents the cost-adjusted physician fee. As is discussed in Section II, financial rewards for C-sections are on average higher than for vaginal deliveries (i.e., $\omega_c > \omega_v$).[16] $f_j(\cdot)$ 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. In other words, $\frac{\partial f_j(\omega_k)}{\partial \omega_k}$ is decreasing in physician wealth. The second component in (3), $b_k(X_i)$, 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

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

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). $f_j(\omega_c) - f_j(\omega_v)$ on the right-hand side are the differences in physician's personal earnings between C-sections and vaginal deliveries, respectively. A C-section is chosen if its financial incentives 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

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

The Role of Physician Financial Shocks. For the purpose of this paper, physician fees ω_c and ω_v are both exogenous parameters. For a given patient (i.e., conditional on patient characteristics X_i),

[16] Admittedly, this is a parsimonious representation of the financial incentives. There could be other benefits and costs associated with C-sections such as malpractice risks, opportunity costs, and resource use. For simplicity, one can think that these factors are already adjusted in ω_k. For example, Medicare's physician fees are determined by the Resource-Based Relative Value Scale system, which accounts for time, skill and effort to provide a service, practice expenses, and malpractice insurance premiums.

physician financial shocks (e.g.,, exogenous changes in W_j) can affect the probability of C-section through different mechanisms.

The first mechanism is the wealth effect per se, or the diminishing marginal utility of income. One example of $f(\cdot)$ that exhibits such property is the constant relative risk aversion (CRRA) utility, $f_j(\omega_k) = \frac{(W_j+\omega_k)^{1-\gamma}}{1-\gamma}$, where W_j is the initial wealth level of physician j, and γ is the coefficient of relative risk aversion. It is easy to see that $\frac{\partial f_j^2(\omega_k)}{\partial \omega_k \partial W_j} = -\gamma(W_j + \omega_k)^{-\gamma-1} < 0$. For instance, as physicians' housing wealth decreases, their marginal utility of income increases, which in turn motivates them to earn additional profits. However, A feature of this mechanism is that it affects the probability of C-section in both directions. In other words, a positive shock that increases physician wealth would persuade physicians to perform fewer C-sections.

Another possible mechanism is financial distress, which unlike the wealth effect, only kicks in when the physician experiences a loss in personal wealth. If the physician's financial health deteriorates to a certain level, their desire to recoup lost wealth may increase due to loss aversion and pursuit of reference income (Rizzo and Zeckhauser, 2003; Goette et al., 2004). At the same time, physicians under liquidity constraints may be especially concerned about the negative consequences in addition to wealth losses, such as costs of mortgage default, foreclosure, or even personal bankruptcy (Bernstein, 2021; Dimmock et al., 2021; McCartney, 2021). As a result, they may therefore resort to the more lucrative treatment option and legally safer option.

V.B Distinguishing the Mechanisms

As is discussed in the previous subsection, the mechanism of financial distress is muted when the physician's wealth increases, whereas the wealth effect is always in play no matter under positive or negative wealth shocks. In the following subsection, I first provide evidence regarding positive wealth shocks and rule out the possibility that the wealth effect plays a major role in explaining the increase in C-section rate. Next, I show that effects are stronger for physicians who have more leverage in their properties and more limited financial capacities, which is consistent with feer of real stakes causing physician financial distress.

Asymmetric Responses. A finding of asymmetric responses to positive and negative financial shocks would lend support for the financial distress mechanism being more relevant than the wealth effect. Recall that the main analysis which has used a sample period from 2007 to 2009, a period when the Great Recession gradually set in and caused a significant decline in housing prices. Table 7, on the other hand, reports results for two alternative sample periods when property values were increasing. In Columns (1) to (3), 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 7 report the regression results which preserve all specifications from Equation (2). Estimates for this alternative sample period are statistically insignificant and small in magnitude, no matter for the average, unscheduled, or scheduled C-section rates.

I also examine a post-crisis period when house prices recovered. In the data, most physicians began to see positive housing returns again since 2013. Such a trend is also consistent with findings by the Federal Housing Finance Agency (FHFA) that Florida's House Price Index hit the post-crisis low in mid-2012 and started to rebound thereafter. By the end of 2018, the House Price Index almost returned to the pre-crisis peak (FRED, 2018). Columns (4) to (6) of Table 7 report the results for the post-crisis period from 2013 to 2015.[17] Again, none of the estimates are statistically significant. Finally, the insignificant estimates persist even in the sample of low-risk births, as is shown in Panel B of Table 7. Take together, these results suggest that physicians do not respond to positive housing shocks by performing fewer C-sections.

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). The asymmetric nature of physicians' responses to financial shocks perhaps partially explains why C-section rates remain stubbornly high even after the crisis, as providers are less subject to financial distress in economic upturns. At the face value, this finding can be explained by the behavioral theory of loss aversion (Tversky and Kahneman, 1991; Genesove and Mayer, 2001), which posits that individuals weigh losses more than equivalent gains. Although I cannot rule out this possibility, the additional evidence in the following subsection suggest that the financial distress is likely driven by real financial stakes as physician behavior changes across the threshold of liquidity constraint.

Physicians' Loan-To-Value Ratios. Physicians in greater debt are economically more vulnerable and in greater financial distress. C-sections become even more attractive to these physicians as it provides higher payments and therefore more liquidity. Moreover, C-sections can potentially serve as a strategy of defensive medicine to financially distressed physicians who are less able to afford malpractice lawsuits, reputational damage, or even job loss. Building on this prediction, I hypothesize that the effect of negative housing shocks is more pronounced 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 (1) to (3) of Table 8 report the

[17] The Florida data that I have access to stops at 2015-Q3. However, there is no obvious reason for why physician responses would be different after 2015. Results for 2010 to 2012 are consistent with the main results.

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 liquidity constraint or fear of default being important in explaining physicians' responses. Columns (4) to (6), on the other hand, show that physicians with safe LTV ratios (i.e., smaller than 90%) respond less significantly and only in the unscheduled C-section margin.

To summarize, the asymmetric effects for positive and negative shocks and the larger effects for highly-leveraged physicians point to financial distress as a major mechanism through which physicians' financial health affects their treatment choices. Admittedly, other factors—such as psychological costs (Currie and Tekin, 2015; Engelberg and Parsons, 2016)—could correlate with or even exacerbate the effect of financial distress in contributing to higher C-section rates. The findings here are also not completely ruling out the wealth effect, although back-of-the-envelope calculations suggest that the physicians were unlikely to completely recoup their wealth losses.[18]

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. Physicians' responses to financial shocks appear to concentrate in the margin of delivery mode instead of the extensive margin of patient volume. Moreover, I find no evidence that patient health outcomes are substantially affected. I interpret these findings through a conceptual framework that incorporates financial incentives and patient welfare as key drivers of physician decision-making. The framework predicts two channels through which negative financial shocks may encourage more C-sections: the wealth effect and financial distress. Evidence points to financial distress as the dominant mechanism, as physicians do not respond to positive wealth shocks, but respond more strongly when in greater liquidity constraints.

Regarding policy implications, this paper speaks to the importance of policies that integrate financial literacy into medical education, as well as federal programs aimed at improving physicians' financial resilience, including the Public Service Loan Forgiveness program and the Income-

[18] 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 a small fraction of their wealth losses but is indeed consistent with the finding in Gruber and Owings (1996).

Driven Repayment plan which will be mostly phased out by July 2026 under the One Big Beautiful Bill Act, as well as The results in this paper suggest that these initiatives may prevent physicians from sliding into financial distress and, in doing so, support healthcare delivery. The weak evidence for the wealth effect per se also aligns with prior research which documents that substitution effects often dominate income effects in physician behavior, and therefore emphasizes the effectiveness of physician payment regulation. Finally, this paper sheds light on how financial market frictions can spill over to clinical decision-making. While I focus on housing wealth shocks, real estate is not the only source of financial risk. Other risks, such as stock market volatility and student loan repayment, may also affect physicians' behavior. Investigating how medical professionals and other skilled workers respond to other but equally significant financial shocks represents an interesting direction for future studies.

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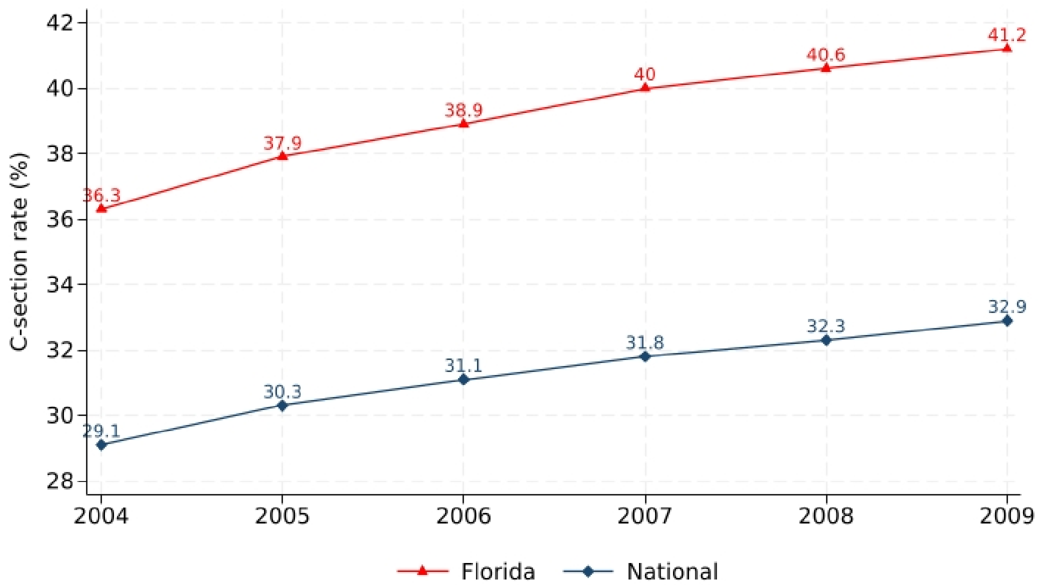
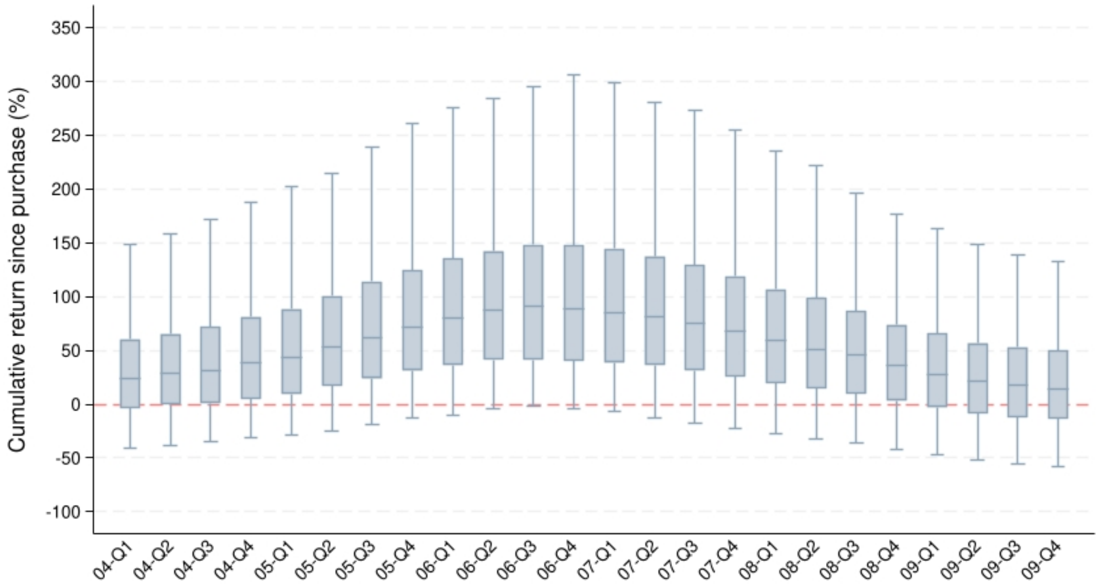
Figures and Tables

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



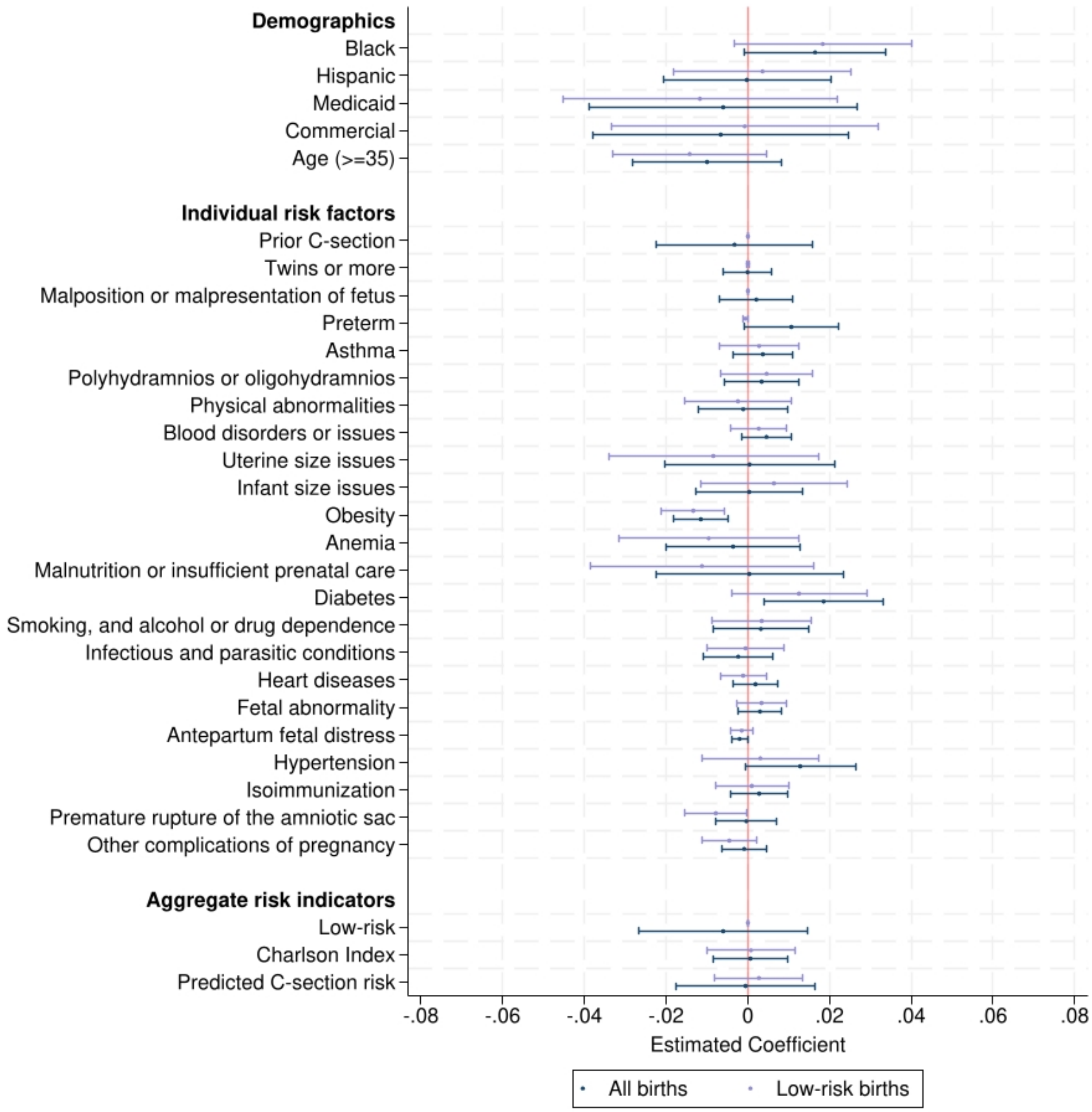
Notes: This figure shows C-section rates in the U.S. and Florida from 2004 to 2009. National rates are sourced from the CDC's Natality Database (see `https://wonder.cdc.gov/natality.html` for details). Florida rates are calculated using hospital inpatient data from the Florida Agency for Health Care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

Figure 2. Distribution of Physician Housing Returns



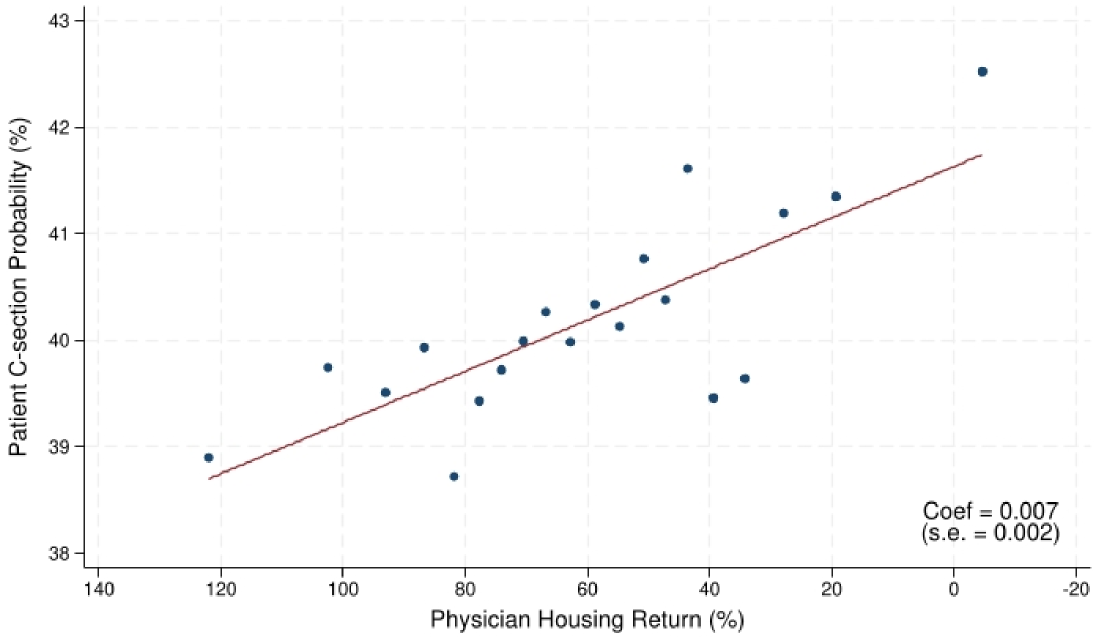
Notes: This boxplot shows the distribution of housing returns among physicians for each quarter from 2004 to 2009. Physician homeowners are identified using CoreLogic data. Housing returns are calculated as cumulative returns since the time of purchase, based on the Zillow Home Value Index, and are expressed 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*		*Matched physicians*	
	Mean	SD	Mean	SD
Panel A: Patient-level variables				
Individual characteristics				
Age	27.759	[5.997]	27.983	[5.975]
Black	0.195	[0.396]	0.212	[0.409]
Hispanic	0.217	[0.412]	0.193	[0.394]
Medicaid	0.495	[0.500]	0.444	[0.497]
Commercial	0.420	[0.494]	0.476	[0.499]
Weekend delivery	0.171	[0.376]	0.171	[0.377]
Individual risk factors				
Prior C-section	0.200	[0.400]	0.194	[0.395]
Malposition or malpresentation of fetus	0.046	[0.209]	0.046	[0.210]
35 years of age or older	0.154	[0.361]	0.159	[0.366]
Twins or more	0.016	[0.125]	0.017	[0.128]
Preterm	0.066	[0.248]	0.068	[0.252]
Asthma	0.027	[0.161]	0.026	[0.160]
Polyhydramnios or oligohydramnios	0.034	[0.180]	0.035	[0.183]
Physical abnormalities	0.059	[0.235]	0.059	[0.236]
Blood disorders or issues	0.021	[0.143]	0.022	[0.147]
Uterine size issues	0.227	[0.419]	0.229	[0.420]
Infant size issues	0.055	[0.228]	0.060	[0.237]
Obesity	0.024	[0.153]	0.025	[0.155]
Anemia	0.083	[0.276]	0.085	[0.278]
Malnutrition or insufficient prenatal care	0.245	[0.430]	0.247	[0.431]
Diabetes	0.061	[0.239]	0.062	[0.242]
Smoking, and alcohol or drug dependence	0.071	[0.257]	0.071	[0.257]
Infectious and parasitic conditions	0.030	[0.170]	0.031	[0.172]
Heart diseases	0.010	[0.099]	0.010	[0.102]
Fetal abnormality	0.013	[0.112]	0.013	[0.115]
Antepartum fetal distress	0.003	[0.055]	0.003	[0.059]
Hypertension	0.082	[0.275]	0.084	[0.277]
Isoimmunization	0.022	[0.147]	0.025	[0.155]
Premature rupture of the amniotic sac	0.031	[0.174]	0.031	[0.173]
Other complications of pregnancy	0.017	[0.128]	0.016	[0.127]
Aggregate risk indicators				
Low-risk	0.708	[0.455]	0.711	[0.453]
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×year-quarter fixed effects. Columns (3)–(5) additionally include patient zip code×year-quarter fixed effects. Panels A and B report results for all patients and for low-risk patients, respectively. Standard errors, clustered at the physician level, are shown in parentheses.

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 Other Treatment Margins

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

Panel B: Low-risk patients	*Induction*	*Vacuum/Forceps*	*Hosp. charges*	*# Deliveries*
	(1)	(2)	(3)	(4)
Physician housing return	-1.154	0.998	0.003	-0.045
	(1.117)	(0.559)	(0.008)	(0.060)
Year-quarter FE				X
Physician FE	X	X	X	X
Patient covariates	X	X	X	
Hospital-year-quarter FE	X	X	X	
Patient zip code-year-quarter FE	X	X	X	
Mean (dep. var.)	22.15	5.62	9.26	41.78
Observations	133,551	133,551	133,551	5,637

Notes: This table reports results from regressions of other treatment margins on physician housing returns. The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. Columns (1) and (2) use indicators (scaled by 100) for labor induction and vacuum/forceps use, respectively. Column (3) uses logged hospital charges 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.

Table 6. Effects on Maternal Health Outcomes

Panel A: All patients

	Length of stay				*Complications*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total	Pre-birth	Post-birth	Prolonged	Hemorrhage	Infection	Laceration	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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total	Pre-birth	Post-birth	Prolonged	Hemorrhage	Infection	Laceration	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 7. Effects of Positive Wealth Shocks

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

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

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

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

Panel A: All patients

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

Panel B: Low-risk patients

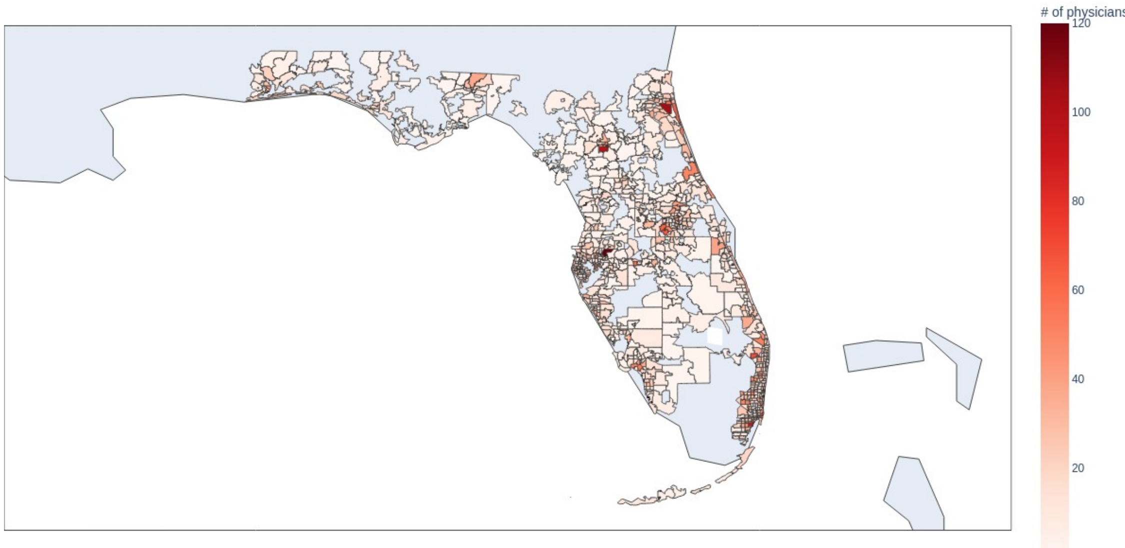
	Physicians LTV: ≥ 90%			*Physicians LTV: < 90%*		
	(1)	(2)	(3)	(4)	(5)	(6)
	C-section	Unscheduled C-section	Scheduled C-section	C-section	Unscheduled C-section	Scheduled C-section
Physician housing return	13.488	8.819	4.669	1.706	3.245	-1.539
	(5.622)	(4.860)	(4.382)	(1.553)	(0.989)	(1.137)
Patient covariates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

Notes: This table reports results from subsample regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since purchase and are reversed in sign. C-section indicators are scaled by 100. Columns (1)–(3) include patients whose physicians have an Loan-To-Value (LTV) ratio higher than or equal to 90%; Columns (4)–(6) include those with an LTV ratio smaller 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.

Online Appendix

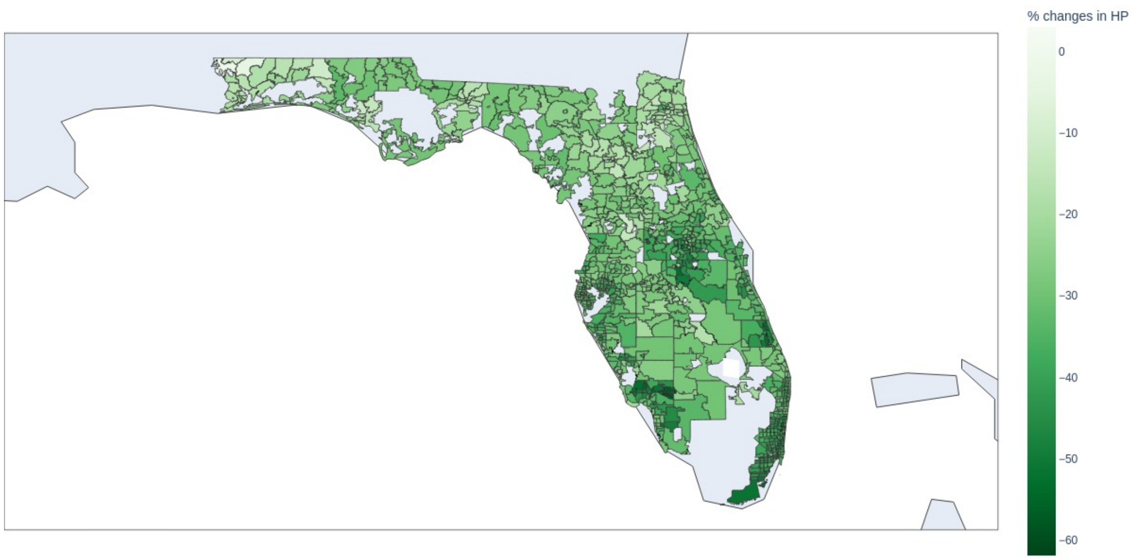
A Additional Figures and Tables

Figure A1. Number of Physicians in Each Zip Code



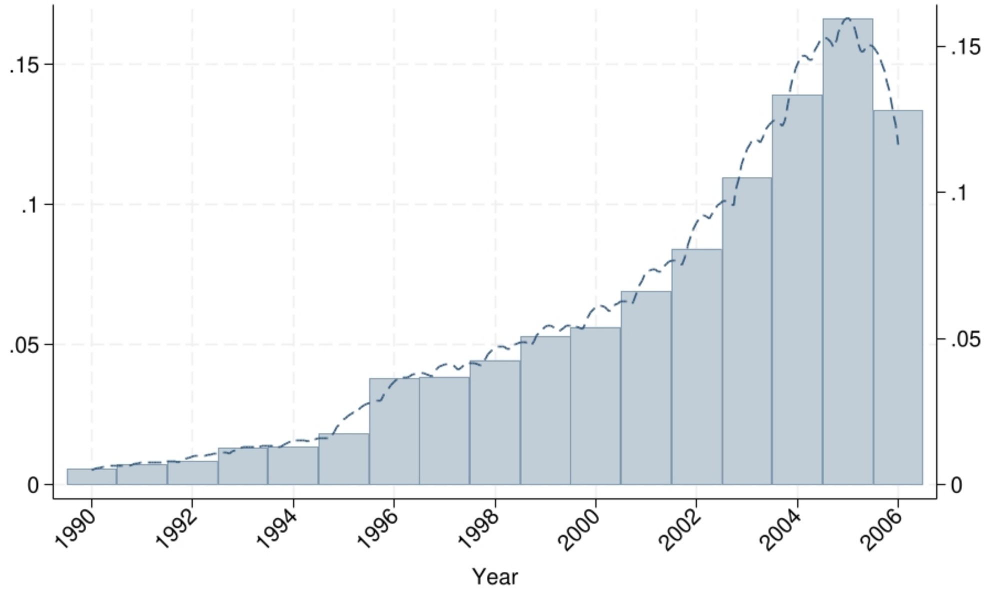
Notes: This figure shows the number of physicians residing in each Florida zip code. Physicians' residences are identified following the procedures described in Appendix B. Only houses held at the end of 2006 are included (i.e., excluding houses sold before 2006 or purchased after 2007). Zip codes with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

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



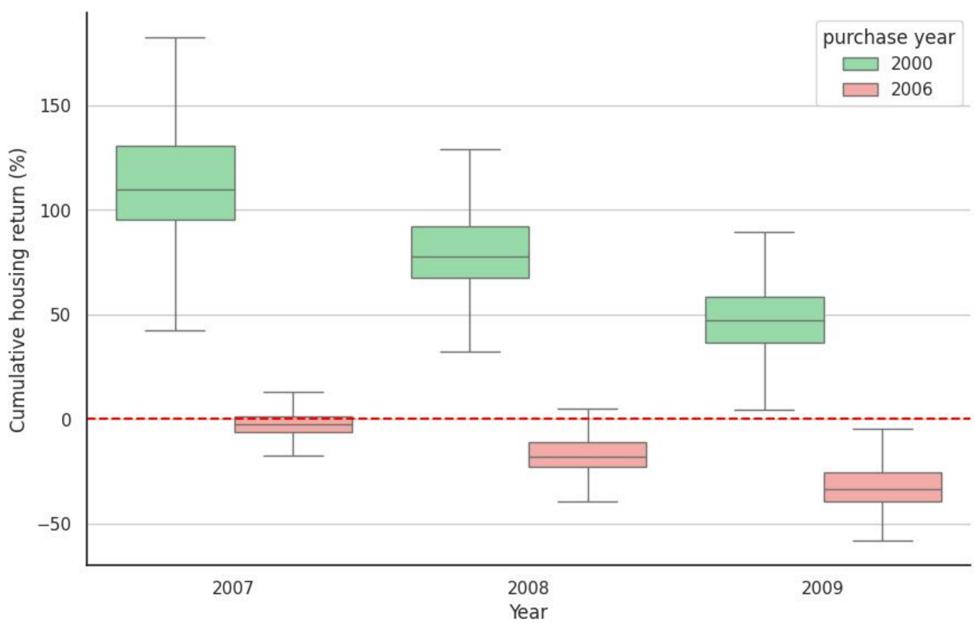
Notes: This figure displays the percentage change in the Zillow Home Value Index (ZHVI) for each Florida zip code from 2007 to 2009. Zip codes with missing ZHVI data are excluded.

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. Effects on Other Treatment Margins, by Delivery Mode

Panel A: All patients

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

Panel B: Low-risk patients

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

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

Table A3. Effects on Length of Stay, Poisson Model

Panel A: All patients

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

Panel B: Low-risk patients

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

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

Table A4. Alternative Clustering of Standard Errors

Panel A: All patients

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

Panel B: Low-risk patients

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

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

Table A5. Extended Fixed Effects to Rule Out Other Selection Channels

Panel A: All patients

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

Panel B: Low-risk patients

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

Notes: This table presents results from patient-level regressions of the C-section indicator on physician housing returns, estimated using a linear probability model as specified in Equation (2). The sample spans 2007 to 2009. Housing returns are calculated as cumulative returns since the time of purchase and are reversed in sign. The C-section indicator is scaled by 100. Column (1) restricts the sample to patients whose residential zip code is within 10 miles of their hospital's zip code. Column (2) adds patient zip code×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 A6. Alternative Measures of Real Estate Shocks

Panel A: All patients

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

Panel B: Low-risk patients

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

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

Table A7. Alternative Sample Specifications

Panel A: All patients

	Allow physicians' entries/exits			Allow time-varying house portfolios		
	(1) 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/mqasearchservices/healthcareproviders/practitionerprofilesearch

[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.

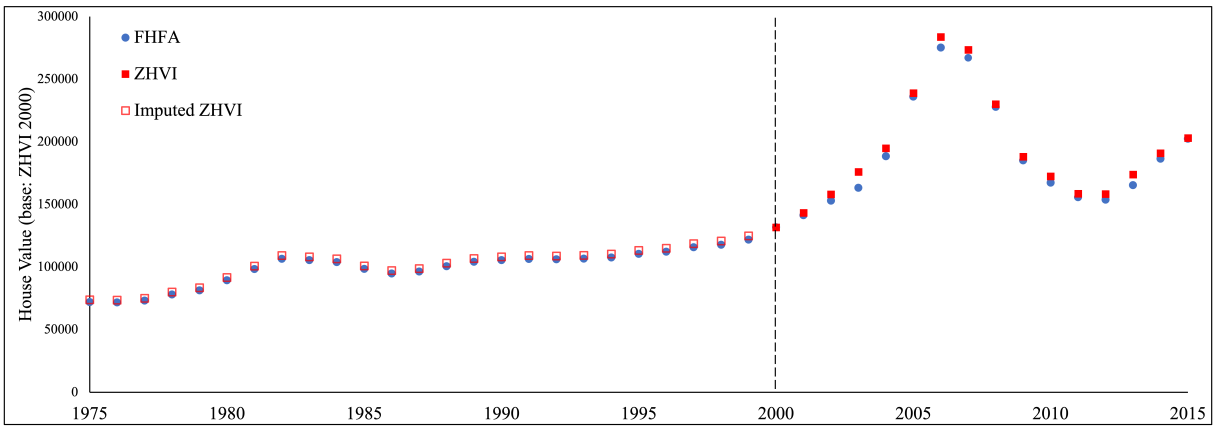
After this step, I drop physicians who have transacted more than 10 different houses over the years, as these are likely poor matches caused by common names. Lastly, I merge in mortgage information. This final step does not result in any loss of observations. Houses without matched mortgage records are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

House Price Index. The Zillow House Value Index (ZHVI) is only available starting from the year 2000.[5] 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

[5] https://www.zillow.com/research/data/

Finance Agency (FHFA) house price index.[6] 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



[6] https://www.fhfa.gov/data/hpi