Wealth Shocks and Physician Behavior: Evidence from Childbirth

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Abstract

Little is known about how physicians are sensitive to their personal wealth although this sensitivity is key to evaluating the effectiveness of price regulations and alternative payment models. Using data on physicians' housing returns linked to their treatment choices, this paper provides new empirical evidence on physicians' responses to wealth shocks and studies the consequent implications on medical expenditure and patient health. Specifically, I look at obstetricians who have substantial discretion and significant financial incentives in choosing cesarean sections over vaginal deliveries. For identification, I rely on the variation in obstetricians' housing returns arising from the Great Recession, depending on when or where they purchased their houses ex-ante. Using a patient-level regression model with obstetrician fixed effects, I estimate that a one-standard-deviation decrease in obstetricians' housing returns leads to an increase of 1.8 percentage points, or 4.5%, in the C-section rate, which further leads to longer in-hospital stays and higher infection rates among the patients. Finally, I show in two counterfactuals that physicians' sensitivity to wealth is useful in predicting changes in the C-section rate under an "across-the-board" fee cut and a transition from Fee-For-Service to capitation.

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1 Introduction

Physician behavior is one of the central issues in the health economics literature (Arrow, 1963; McGuire, 2000). Prior studies have shown that physicians are responsive to financial remuneration under the volume-based payment schemes (Rice, 1983; Gruber et al., 1999; Clemens and Gottlieb, 2014; Brekke et al., 2017). However, little is known about how physicians' personal *wealth* affects their behavior, although physicians are reported among the top-percentile earners in the country (Gottlieb et al., 2020). For one thing, a considerable amount of wealth in physicians' portfolios is tied to financial assets. Volatile returns on these assets can expose physicians to unpredictable wealth shocks through booms and busts.[1] For another, physicians are often haunted by significant amounts of personal debt such as student loans and house mortgages, especially early in their careers.[2] Expenses associated with these liabilities could put physicians into non-trivial financial distress or even burnout (West et al., 2011).

Physicians' sensitivity to wealth is also important in understanding policy interventions that leverage prices (i.e., physician fees) to achieve targets of medical expenditure and health outcomes. Most papers in this realm estimate physicians' responses to changes or variations in physician fees directly. However, these estimates fail to disentangle two counter forces, *substitution effect* and *wealth effect* (McGuire and Pauly, 1991). The substitution effect suggests that a lower fee for a specific service might reduce its relative attractiveness and shift physicians' interest to more profitable alternatives. On the contrary, the wealth effect implies that a lower fee creates a *de facto* loss in physicians' wealth, motivating more work and/or use of more expensive services.[3] The relative importance of the wealth effect (as opposed to the substitution effect) in determining physicians' responses depends on their sensitivity to wealth. Without directly estimating this sensitivity and separating the two opposing effects, it is difficult to evaluate the effectiveness of a specific price regulation.

This paper aims to empirically estimate the effect of physicians' wealth on their behavior (specifically, treatment intensity), and study the consequent policy implications on medical expenditure and patient health. However, there are at least two challenges in directly estimating this effect. The

[1] According to Medscape's Physician Wealth and Debt Report (2021), about a third of physicians had a significant financial loss in 2020, the onset of the COVID pandemic and the following economic turmoils. Among the specialists who admitted making investment mistakes, 44% invested in either stock or real estate assets that turned out badly. See https://www.medscape.com/slideshow/2021-compensation-wealth-debt-6013910.

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

[3] This is also called the income effect. In this paper, I use "wealth effect" and "income effect" interchangeably.

first one is the lack of reliable measures of physicians' wealth. Previous studies have relied on cross-sectional survey data on physicians' earnings, which are inevitably subject to endogeneity issues (e.g., Rizzo and Blumenthal (1994)). Physicians who report more wealth could be fundamentally different from those who report less. It is therefore hard to tell if the detected difference in physician behavior is driven by the effect of wealth or unobserved heterogeneity at the physician level. Second, physicians' treatment decisions could be confounded by patient demand. For example, healthcare markets are fairly local, so physicians' wealth shocks could be correlated with their patients', which further affects patients' underlying health and preferences (McInerney et al., 2013; Yilmazer et al., 2015; Fichera and Gathergood, 2016). Breaking this simultaneity usually requires explicitly controlling for detailed demand factors at the patient level such as risk factors, which are often missing in the data used by previous studies (e.g., Gruber and Owings (1996)).

To overcome these challenges, this paper uses linked data on physician housing returns and treatment choices and provides new empirical evidence on the sensitivity of physicians' behavior to their wealth. I take advantage of a large-scale real estate database that encompasses physicians' real estate holdings and construct a physician-level time-varying measure of housing return during the Great Recession (2007–2009). An average physician lost about 20% of her home value in this period, which is a sizable shock to a physician's wealth considering that households of comparable income levels hold about 20% of wealth in the real estate sector (Survey of Consumer Finance, 2009). Critically, there is also substantial variation in wealth shocks across physicians depending on where and when they bought their houses. The home value at the end of the period, compared to the beginning, decreased by 31.8% for a physician at the 25th percentile but only 6.5% for another at the 75th percentile. For the purpose of identification, note that physicians' house-purchasing decisions were made before the recession which they were not able to foresee. Therefore, I argue that physicians' housing returns, once conditional on their pre-decided housing portfolio, are mainly driven by the business cycle and unlikely to be correlated with patient treatments after the recession began. With this assumption, I estimate a patient-level regression model with *physician fixed effects*. This design therefore has the advantage of teasing out the physicians' sensitivity to wealth from other time-invariant confounds such as their diagnostic and surgical skills.

I focus on the inpatient setting of labor and delivery, or childbirth, which has two key advantages for my purposes.[4] First, obstetricians are equipped with large discretion and patients' preference plays a minimal role in deciding what type of treatment a patient receives (Gruber and Owings, 1996; Johnson and Rehavi, 2016).[5] I also link the physician-level data to the Florida hospital inpatient discharge data which contains variables of patient demographics and ICD codes for patients' comorbidities. This makes it possible to construct and conditional my identification on a comprehensive set of indicators for patients' riskiness. Moreover, the inpatient data reveals the patient's zip code which allows me to additionally control for patients' wealth shocks. Obstetricians' housing returns are uncorrelated with the observed patient covariates after controlling for obstetrician fixed effects. In other words, obstetricians who lost more wealth do not tend to treat patients who are riskier.

The other advantage of focusing on labor and delivery is that the main treatment margin (i.e., the measure of physician behavior) is well defined in this setting — obstetricians choose whether to perform a more intensive procedure (cesarean section, or C-section) or a less intensive one (vaginal delivery) for a given patient. It has been widely documented that obstetricians are faced with significant financial incentives for performing cesarean deliveries over vaginal ones. For instance, the physician fee for a C-section is about 15% higher than that of a vaginal delivery, for both commercial and Medicaid patients (Corry et al., 2013). Therefore, I hypothesize that obstetricians are more willing to perform C-sections when exposed to negative wealth shocks as lower wealth increases their marginal utility of income.

Consistent with this hypothesis, I find that a one-standard-deviation decrease in obstetricians' housing returns leads to an increase of 1.8 percentage points in the probability of C-section, which is a 4.5% increase compared to the average. This effect is non-trivial and explains over 80% of the C-section rate increase in Florida during the period of 2007–2009. The increase in the C-section rate concentrates on low-risk births, unscheduled C-sections, and C-sections without attempts of other ancillary procedures. This effect is also heterogeneous across different patient groups. For example, black patients are more likely to be affected by their obstetricians' wealth shocks. I also find that physicians who are in significant financial distress, who practice in less competitive markets, and who used to perform more C-sections, are more responsive to declining housing wealth. Lastly, I do not find evidence that obstetricians respond by delivering more births, possibly because the extensive

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

[5]Medical doctors who specialize in this particular clinical setting include obstetricians and gynecologists. For the sake of simplicity, I use obstetricians to refer to both throughout the paper.

margin is largely determined by other factors such as the fertility rate.

I find that the increased C-section rate can have adverse consequences on patient health. Specifically, patients' length of in-hospital stay increases, which is mainly driven by longer stays after, instead of before, the delivery. I also find that physicians' wealth shocks raise patients' probability of catching an infection during their inpatient stays. A one-standard-deviation decrease in obstetricians' housing returns leads to a 0.25 percentage-point increase (or a 28% increase from the mean) in the infection rate. These results are consistent with the fact that C-sections are more invasive and require longer recovery time than vaginal deliveries.

Several results justify the causal interpretation of my findings. This interpretation requires the identification assumption that matching between physicians and patients is as close as being random because physicians' *ex-ante* housing decisions should be irrelevant to their treatment choices *ex-post*. This assumption can fail if, for example, patients of different riskiness and preferences could selectively sort themselves into physicians with different wealth shocks. Alternatively, hard-hit physicians could cherry-pick patients who demand C-sections. Even though patient characteristics are balanced across physicians' wealth shocks, selection could arise on patient-level *unobservables*. To alleviate this concern, I further control for patient zip code$\times$time and physician$\times$patient zip code fixed effects. These fixed effects help to address that patients living in certain zip codes develop worse health conditions over time that are diagnosed by the obstetrician but unknown to the econometrician, and that some obstetricians are better at attracting and treating patients from certain zip codes.

I then show that other supply-side channels cannot explain my results. An example of such channels could be that hospitals also experience wealth shocks and therefore have extra financial incentives to encourage more intensive treatments (Dafny, 2005; Dranove et al., 2017; Adelino et al., 2022). The estimate of physician wealth shocks could be overestimated if hospital-level incentives are passed through to physicians. I show that my results are robust to the inclusion of hospital$\times$time fixed effects, and therefore independent of supply-side responses beyond those at the physician level. Lastly, how long physicians have become homeowners and started to pay mortgages can also affect their wealth accumulation, risk attitudes, and thus treatment behavior. Physician fixed effects alone would fall short of accounting for the possibility that those who settled down earlier (e.g., those who are more senior) gradually become more (or less) willing to perform C-sections over time. I then try to additionally control for *purchase time*$\times$*focal time* fixed effects and my results remain the same.

Given these empirical estimates, I show how isolating the wealth effect can be useful in evaluating the effectiveness of price regulations and payment reforms. I first use a simple model to illustrate that physicians' sensitivity to wealth is embedded in the uncompensated price effect on physician behavior through the Slutsky Equation. Next, I study two counterfactuals associated with changing physician fee schedules. The first one is an "across-the-board" price reduction under the Fee-For-Service scheme where physician fees are lowered by the same amount for all services. This is a blunt way of price regulation, yet commonly seen in policies such as Medicare's Sustainable Growth Rate (SGR) formula for annual updates of physician fee schedule (Congressional Budget Office, 2006). Such policy intervention effectively shuts down the substitution effect since the relative attractiveness between different services (i.e., pay differential) remains intact. As a result, the wealth effect alone determines the changes in physician behavior. I find that physicians are more likely to adopt the more profitable and more intensive option — a 10% universal fee cut is enough to increase the C-section rate by 1.68 percentage points. This change then compromises the realized cost-savings by additionally increasing spending about $7.8 per newborn and over $31 million per year. Such "volume-offset" effect at the intensive margin should therefore raise a red flag for payers and policymakers such as the Congressional Budget Office.

The second counterfactual relates to a compensated price change. Examples include the *transition* from the current Fee-For-Service scheme to a bundled payment or a vertical integration model where the physicians are paid a lump-sum price which is irrelevant to the ex-post treatment choices. An interesting feature of transitions into these payment models is that only the substitution effect is at play because the lump-sum price is usually benchmarked using provider-specific average historical spending (i.e., income compensation). Combining the estimated price effect from the literature and my estimated wealth sensitivity, I uncover the size of the substitution effect. I find that the magnitude of the wealth effect is about 30% as large as that of the substitution effect in the Slutsky Equation. If the payment structure transitions from Fee-For-Service to capitation of uniform rates, the C-section rate would be at most 1.76 percentage points (or 6.1% compared to the current level) lower. Put differently, ignoring the wealth effect (i.e., using the uncompensated price effect only) would underestimate the decrease in the C-section rate by about 23%.

This paper contributes to three strands of literature. First, it enriches the knowledge of how physicians respond to financial incentives by directly estimating the wealth sensitivity of healthcare providers. The wealth effect is key to reconciling the so-called "backward-bending" labor supply curve for physicians documented in the early literature (Rice, 1983; Christensen, 1992; Nguyen and Derrick, 1997) and more recent finding that the physician service provision increases in physician fees (Yip, 1998; Clemens and Gottlieb, 2014; Coey, 2015). Few studies directly estimate the wealth effect, with Rizzo and Blumenthal (1994) being a notable exception where they use non-practice income (education indebtedness and spouse's income) together with wage rate to explain physicians' hours of work. They find a significant wealth effect that offsets almost 40% of the compensated wage effect. However, the cross-sectional physician survey data that they use makes their identification inevitably subject to omitted variable bias. My study contributes by taking advantage of a unique quasi-experiment (i.e., the Great Recession) to estimate the same effect from changes in physicians' housing wealth.[6] Detailed variables on patient demographics and risk factors also help control for confounds on the demand side which is nearly impossible without claim-level data.[7]

Gruber and Owings (1996) and He et al. (2015) are also close to the current study. Gruber and Owings (1996) find that obstetricians substitute from vaginal to cesarean delivery in the wake of lower earnings because of declining fertility rates at the state level. He et al. (2015) find that physicians whose earnings are more affected by the rise in county-level unemployment rates switch to serving more Medicare patients. In contrast, my measure of physicians' housing returns provides variations that are arguably uncorrelated with physicians' professional earnings, so my identification is less likely to be contaminated by the unobserved practice style of physicians. Focusing on the clinical setting of childbirth also allows me to reasonably measure patient outcomes and investigate the health impacts of physician behavior, which are missing in both Gruber and Owings (1996) and He et al. (2015).

Second, this paper is related to the literature on recession and health. Ruhm (2000, 2003, 2005) and Finkelstein et al. (2023) have shown that state- or individual-level mortality rates fall in times

[6]Studies in the literature of labor economics also look at how wealth shocks affect workers' behavior using data from surveys, lottery windfalls, casino profits, etc (Krueger and Pischke, 1992; Imbens et al., 2001; Cesarini et al., 2017; Jones and Marinescu, 2022). Compared to them, this paper leverages detailed data from a specific profession (i.e., physicians) who generally have a higher income level, a longer process of human capital accumulation, and looks at how physician behavior can potentially produce greater externalities to the downstream patients.

[7]Similarly, Dimmock et al. (2021) find a negative relation between financial advisors' housing returns and their misconduct. However, they are unable to perform an advisor-client encounter level analysis or control for customers' characteristics. Several other papers in the finance literature also link workers' housing returns to their performance (Pool et al., 2019; Maturana and Nickerson, 2020; Bernstein et al., 2021; Aslan, 2022). Compared to them, my work additionally looks at the welfare effect on the downstream consumers.

of higher unemployment rates.[8] Others have provided counter-evidence that health could deteriorate as a result of recession-induced job displacement (Sullivan and Von Wachter, 2009), loss of health insurance (Cawley et al., 2015), and mental health issues that come with wealth loss and financial distress (McInerney et al., 2013; Currie and Tekin, 2015; Engelberg and Parsons, 2016; Schwandt, 2018). Although already fairly extensive, a large body of this literature only seeks to provide justifications from the demand-side responses, leaving the role of healthcare providers unattended. This paper, on the other hand, explores a *supply-side* channel through which physicians subject to unexpected fluctuations in wealth status change their treatment choices, passing through the health consequences to their patients. My finding of longer length of stay and higher maternal infection rate offers a supply-side explanation for why health outcomes could be worse off in economic downturns.

Finally, this paper adds to a small but growing literature investigating how provider financial status affects health outcomes. Aghamolla et al. (2021) discover that hospitals experiencing credit rationing have higher mortality/readmission rates and lower patient satisfaction. Begley and Weagley (2023) find that nursing homes with tighter financial constraints have a harder time investing in staffing and therefore have more deaths during the COVID-19 pandemic. Unlike these studies, I measure exogenous wealth shocks at the *physician* level using data on individual real estate holdings. Furthermore, my data allows me to control for hospital×time fixed effects and therefore isolate the contemporaneous responses at the facility level. There are also papers studying the effect of wealth shocks on hospital behavior. For example, Dranove et al. (2017) find that non-profit hospitals that experienced asset depreciation in the stock market might cut service offerings if not profitable, and Adelino et al. (2022) find that hospitals with greater investment losses during the financial crisis increase the use of more intensive treatments. However, none of them look at outcomes of patient health as this paper does, making them unable to draw welfare implications.

The remainder of this paper proceeds as follows. Section 2 introduces the clinical and institutional setting. Section 3 outlines a conceptual framework that derives the main hypothesis. I discuss the data in Section 4 and the empirical design in Section 5. Section 6 reports the regression results and Section 7 demonstrates the counterfactuals. Finally, Section 8 concludes the paper.

[8] Ruhm's papers attribute the main reason to higher opportunity cost of time and therefore longer working time when the labor market is booming. Follow-up studies, although agreeing on the pro-cyclicity of health, find that decreased mortality among the elderly, instead of the working-age population, drives the mortality decline (Miller et al., 2009; Stevens et al., 2015). Other explanations for counter-cyclical mortality include, for example, less traffic, pollution, and spread of diseases due to reduced economic activities (Chay and Greenstone, 2003; Miller et al., 2009; Adda, 2016; Heutel and Ruhm, 2016).

2 Background

This section introduces the clinical and institutional setting used in testing the effect of wealth on physician behavior—labor and delivery. Childbirth is the most common cause of hospitalization in the U.S.; the 4 million annual childbirth-related hospital stays each year account for more than 10 percent of all inpatient stays (Podulka et al., 2011). The primary treatment choice in childbirth is vaginal delivery versus cesarean section. Among all the newborns, about 1/3 of them are delivered by C-section in the U.S. nowadays (Osterman et al., 2022). This C-section rate has doubled since 1980 and reached a level higher than not only that of most developed countries but also the 10–15% recommended by the WHO (Betrán et al., 2016). There is also a considerable amount of geographic variations in C-section rates across different states (Baicker et al., 2006). The C-section rate in Florida has always been higher than 38% since 2007 and among the highest in the U.S. by 2020.[9] Figure A1 shows the evolution of C-section rates in Florida from 2006 to 2014.

Clinically, a lot of C-sections are performed at the discretion of the obstetricians (Cunningham et al., 2014). The obstetrician can schedule a C-section in advance (usually at week 39) with a patient with clear risk factors (e.g., preterm, breech, multiple fetuses, pinched or prolapsed umbilical cord, etc). Patients with less clear medical needs will enter (or be induced) into spontaneous labor and attempt a vaginal delivery. If medical conditions such as fetal distress and failure to progress arise during the process, the obstetrician would advise an emergency C-section (i.e., an unscheduled C-section).[10] The diagnosis of these conditions and thus the decision of delivery method fall into a clinical gray area and highly depend on obstetricians' training, judgment, and preference. For example, it is an obstetrician's responsibility to weigh the benefits and costs of a C-section on a specific patient and decide how long to allow labor to proceed (Kozhimannil et al., 2014). It is difficult for patients who don't have superior information or medical knowledge to weigh in on the appropriateness of either method, especially in a narrow time frame of delivery. There is also little limitation from insurers given the subjective diagnoses by obstetricians.

Cesarean procedures can be life-saving, especially for patients exhibiting certain conditions. At

[9]Estimated by the author using Florida's hospital discharge data, and by HCCI using patients covered by ESI or Medicaid. See https://healthcostinstitute.org/all-hcci-reports/one-third-of-births-occurred-by-c-section-in-esi-and-medicaid-in-2020-1 for more details.

[10]C-sections can also be performed on maternal request. However, only 2.5% of all births in the United States are estimated to be maternal-requested according to the American College of Obstetricians and Gynecologists' Committee on Obstetric Practice (https://www.acog.org/clinical/clinical-guidance/committee-opinion/articles/2019/01/cesarean-delivery-on-maternal-request).

the same time, although rarely leading to maternal mortality, C-sections increase the risk of maternal morbidity, or complications, such as infection, hemorrhage, and blood clots during and after the delivery. Due to its invasive nature, C-sections often time require a longer length of stay in hospital (2–4 days compared to 1–2 days for vaginal delivery) and recovery time after discharge (6–8 weeks compared to 2–6 weeks for vaginal delivery). They are more likely to be rehospitalized and receive C-sections in future pregnancies as well. C-sections can save infants from the uncertain consequences of prolonged and difficult labor. However, they can also have adverse health impacts on infants through injuries during the delivery and future respiratory and immune system issues. Card et al. (2023) provides a summary of clinical literature on the maternal/infant health effects of C-sections.

The potential overuse of C-sections, especially those on low-risk patients, has therefore raised concerns. Public health agencies and policymakers have been advising providers to lower the use of C-sections. For instance, the Department of Health and Human Services (HHS) has set a target C-section rate for low-risk women to 23.6% by 2030 based on the Healthy People Initiative, 2.7 percentage points lower than the most current level.[11] Financial incentives of obstetricians are cited as a key driver behind the rising adoption of C-sections (Gruber and Owings, 1996; Gruber et al., 1999; Alexander, 2017).[12] There is a well-documented gap in the reimbursement rates for C-sections and vaginal deliveries. The average physician fee for C-sections was about 1/3 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 (Gruber and Owings, 1996; Corry et al., 2013; Alexander, 2017). For example, Corry et al. (2013) use data from MarketScan during 2004–2010, and report that commercial insurers paid \$3,350 and \$2,887 for cesarean and vaginal deliveries as professional service fees, respectively (and for Medicaid, \$1,654 versus \$1,445). Obstetricians can additionally receive higher reimbursements from cesarean-related services (e.g., anesthesiology, laboratory, radiology, and pharmacy fees), and sometimes dividends from their ownership in the facilities, the pay differentials in the professional service fees can be considered as the lower bound of financial incentives in practicality.[13]

[11]See https://health.gov/healthypeople/objectives-and-data/browse-objectives/pregnancy-and-childbirth/reduce-cesarean-births-among-low-risk-women-no-prior-births-mich-06.

[12]Several other factors, including technology advance in diagnosing fetal distress and higher malpractice risks, are also believed to fuel the increase in the C-section rate (Dubay et al., 1999; Grytten et al., 2012; Bertoli and Grembi, 2019).

[13]There are also financial incentives at the hospital level. For example, commercial insurers (Medicaid) paid \$9,933 vs \$6,738 (\$4,358 vs \$3,102) for cesarean and vaginal deliveries as facility fees, respectively. In the empirical analysis, I explicitly control for this hospital-level pay differential.

The pay differential in delivery service constitutes a non-trivial financial incentive to the practitioners. The majority of an obstetrician's income comes from providing health care services such as delivery and postpartum care. According to Gottlieb et al. (2020), the professional earnings of obstetricians in Florida account for about 83.5% of their annual gross income.[14] Moreover, although C-sections are more financially rewarding, they are not necessarily more costly in terms of labor input. A vaginal delivery can be subject to greater uncertainty in terms of waiting time and often requires a few hours of monitoring during the labor. C-sections, on the other hand, typically only last for 45–60 minutes, therefore lowering the opportunity costs and providing "convenience" to the obstetricians (Keeler and Brodie, 1993). Taken together, C-sections are more economically appealing in the eyes of obstetricians—an assumption motivating the empirical analysis later.

3 Theoretical Framework

Here in this section, I consider a conceptual framework of physician decision and the role of physician's wealth. Consistent with the empirical setup, the physician agent in this framework is an obstetrician making a decision in childbirth. However, this framework is general enough to be extended to other settings where a physician makes treatment choices at the intensive margin taking into account both financial incentives and patient well-being. Another example is that cardiologists decide if a heart attack patient should receive open-heart surgery (CABG) or minimally invasive intervention (PCI).

Physician's utility

A typical obstetrician (whose subscript is omitted without loss of generosity) maximizes his/her utility of serving a patient i by choosing a treatment plan k from a choice set, $k \in \{v, c\}$, where v and c denote vaginal delivery and C-section, respectively.

$$\text{Max:} \quad \mathbf{V}_{ik} = \mathbf{V}_{k}^{physician} + \mathbf{V}_{ik}^{patient} = \underbrace{f(w_k)}_{\substack{\text{pecuniary utility for} \\ \textit{physician} \text{ to provide } k}} + \underbrace{g_{ik}}_{\substack{\text{medical benefits for} \\ \textit{patient} \text{ to receive } k}} \tag{1}$$

In Equation 1, w_k is how much treatment k reimburses the physician (in \$ terms). It is assumed

[14] Gottlieb et al. (2020) estimate the professional earnings and gross income for physicians of different specialties using tax form data: `https://www.gottlieb.ca/data/physician_earnings_data.zip`.

that the reimbursement rate of C-section is higher than that of vaginal delivery, i.e., $w_c > w_v$. $f(w_k)$ is the pecuniary utility to the physician from treatment k, capturing the financial incentives for the physician to provide k.[15] g_{ik} is the medical benefits of treatment k specific to patient i. The larger g_{ik} is, the more appropriate for the patient i to receive treatment k, and therefore the more disutility it imposes on the physician if he chooses treatments other than k.[16]

The probability of C-section

I abstract away from the "negotiation" between patients and physicians because patients' opinions in this clinical setting are less pivotal as is discussed in the previous section. Therefore, the treatment choice is up to the attending physician. An obstetrician only chooses C-section (c) for patient i if

$$f(w_c) + g_{ic} \geq f(w_v) + g_{iv} \implies \quad g_i \equiv g_{iv} - g_{ic} \leq f(w_c) - f(w_v) \tag{2}$$

The left-hand side of the inequality 2, g_i, captures the medical appropriateness for patient i to receive a vaginal delivery as opposed to a C-section. The right-hand side is the pay differential between C-section and vaginal delivery for the obstetrician. In other words, when the medical benefit of vaginal delivery is not enough to counter the financial unattractiveness of vaginal delivery, a C-section would be chosen. Equally, g_i represents the upper bound of pecuniary utility the obstetrician is willing to forgo by not performing a C-section.

Assuming $G(\cdot)$ is the *inverse* CDF of g_i, the probability of patient i receiving C-section is therefore given by:

$$p = G\Big[f(w_c) - f(w_v)\Big] \approx G\Big[(w_c - w_v)f'(\overline{w})\Big] \tag{3}$$

where $f'(\overline{w})$ is the marginal utility of income (evaluated at the expected reimbursement rate for an average birth, $\overline{w}$). The *wealth effect* implies that $f'(\cdot)$ decreases in wealth (or lifetime income). In other words, $f''(\cdot) < 0$. This feature of concavity is consistent with the statement that "one more dollar is worth less for a wealthier individual than for a poorer". From here, Equation 3 generates the key prediction of this study: given the payment differential between two treatments $w_c - w_v$, the marginal utility of income $f'(\cdot)$ increases as a physician sees a decline in wealth. As a result, the probability of

[15] To be precise, this represents the *net* benefit to a physician for providing treatment k. In other words, this is pay minus cost, except that the cost parameters are omitted to simplify the analysis.

[16] This disutility is realized through either the physician's "internal conscience" or that patients punish physicians overly performing unnecessary procedures (the so-called "demand reduction" channel).

C-section p also increases. Marginal patients with g_i close to the ex-ante cutoff would be shifted from the vaginal side to the cesarean side because of this wealth effect.

It is just for the heuristic purpose that I only include physicians' earnings from providing a service, w_k, in the pecuniary utility function, $f(\cdot)$. In reality, it is most likely that $f(w) = f(w_k + w_h)$ where physicians value both their professional earnings w_k (e.g., those from delivering babies) and non-professional earnings w_h (e.g., those from housing returns) at the same time. Previous studies use variation or changes in w_k to estimate the curvature of $f(\cdot)$. However, this approach could fail to disentangle two possible reasons why a patient gets more expensive treatment: (1) she needs it because she is sicker, or (2) she receives it because her physician is incentivized to provide it. On the contrary, my estimation relies on exogenous changes in w_h caused by a natural experiment (i.e., the Great Recession) which I argue are unlikely to be correlated with the patient's underlying conditions (i.e., g_i). The assumption required is that professional earnings and non-professional earnings are perfectly substitutable in the eyes of physicians. One might argue that earnings from real estate holdings are less liquid than cash earnings. In that sense, my estimate provides a lower bound for what the actual wealth effect may be.

In the subsequent sections, I show how to empirically estimate the effect of physician wealth on the likelihood of a patient receiving a C-section, holding other factors constant. In section 7, with a more concrete model I demonstrate how this estimate of wealth effect can inform the policymakers in terms of treatment intensity and medical expenditure under different counterfactuals.

4 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 archives inpatient discharges insured by all kinds of payers and recorded by all hospitals in the state. For each inpatient discharge, it provides patient demographics including age, race and ethnicity, gender, insurer, and zip code. I map zip code-level socio-economic conditions such as education and household income to a patient using her home zip code. I identified patients' comorbidities using ICD-9 diagnosis codes and medical service provision through ICD-9 procedure codes. The data also allows me to observe a series of patient outcomes such as length of stay, discharge status, and hospital charges. Lastly, the data contains unique identifiers for the attending and operating physicians of each inpatient. These identifiers are crucial in that they enable me to merge the inpatient records with external data on physician characteristics and real estate holdings. I start by extracting hospital inpatient records related to labor and delivery. I focus on patients who have an age between 18 to 50, stay in the hospital for no more than 7 days, and have no missing demographics. There are 1,829,067 identified childbirths in Florida from 2006Q1 to 2015Q3, among which 713,360 (39%) are delivered by C-sections.

To obtain physician characteristics, I link physicians in the inpatient sample to Florida's healthcare practitioner profiles which include individual information for a number of professions including medical doctors. For each physician, I can observe the physician's full name, gender, mailing, and practice location address. I supplement the practitioner profiles using the National Provider Identifier (NPI) registry of the National Plan and Provider Enumeration System (NPPES). The registry contains physician-level information including specialty, age, graduation date from medical school, etc.

To measure physicians' real estate holdings, I rely on *CoreLogic*, a real estate database tracking housing transactions based on county deed records. CoreLogic has reasonably good coverage of housing transactions since the mid-1990s and is commonly used in the household finance and real estate literature.[17] For each deed record, CoreLogic reveals the date of the transaction, the sale price, the address of the property, the names of both buyer(s) and seller(s), mortgage amount, as well as other house characteristics. I start by restricting the house location to Florida and the house type to one of the following: single-family residence, condominium, commercial, duplex and apartment. I then search for houses ever purchased or sold by physicians in the inpatient sample by buyer/seller names using a combination of "*Last Name + First Name + Middle Name Initial*".[18] A physician is identified as the owner of a matched house from the date of purchase until the date of sale (if he ever disposes of it).

Together, there are 32,457 identified houses ever possessed by 12,578 obstetricians who either attended or operated labor and delivery in Florida during the period in which I have the inpatient data (2006–2015). They account for 88% of all obstetricians during the same sample period.[19] It

[17]Most recent examples include Bernstein et al. (2021) and Aslan (2022), among others.

[18]Common names with an abnormal number of matches are dropped in order to reduce the matching error. Appendix B documents the detailed procedures of my searching algorithm and validation identified physicians' houses. **Physicians' names and other individual information considered private and sensitive will be neither disclosed throughout this project nor used for other purposes**.

[19]Note that these obstetricians include those who join the physician labor force after the beginning of the sample period

is possible that a physician can have multiple matched properties. By the end of 2006, 68% of the matched physicians have a matched house, 20% of them have two, 7% have three, and 5% have four or more. 73% and 70% of obstetricians have at least one house in the same region where most of their patients come from and where their main hospitals are located. 50% and 47% of obstetricians' houses are in the same region where most of their patients come from and where their main hospitals are located. Physicians with no matched properties can either be renters or homeowners whose deeds are missed out by CoreLogic. Appendix B provides further details about the outcomes of this search process.

In the main analyses, I focus on the onset of the Great Recession, namely, 2007–2009. I save the subsequent years for a separate analysis to test if there is a long-term and asymmetric effect of housing wealth in times of stagnation and recovery. To this end, I restrict the main sample to a group of physicians who are identified as homeowners by the end of 2006. Physicians may strategically buy or sell houses in the wake of the forthcoming crisis. I therefore fix their housing portfolios at a snapshot of 2006/12/31 and use these portfolios to construct the measure of wealth shocks. I also focus on physicians who have already started practicing since 2006 (i.e., before the recession), and keep practicing until at least 2009. I keep attending physicians who are doctors and drop births delivered by nurses and midwives. I also drop patients whose attending physicians are not the ones who perform the deliveries (i.e., the operating physicians) and attending physicians who never perform C-sections during the sample period. This step excludes the cases where the obstetricians are not equipped with the skill set to perform C-sections and therefore have to bring in external surgeons. Finally, I drop inactive physicians whose number of deliveries is fewer than the 1st percentile of all physicians.

These filters leave me with 487 physicians delivering 187,034 births in the analytical sample. Table 1 reports the descriptive statistics for both the analytical sample with matched physicians and the leave-out sample where the physicians are not matched. Patients are fairly similar across the two samples along the dimensions of demographics, insurance types, and clinical risk factors. Obstetricians in the two samples are also comparable in terms of gender, tenure, workload, and C-section rate. For obstetricians in the analytical sample, they have on average 1.4 houses and have owned the houses for about 5 years by the end of 2006.

and who retire before the end of the sample period. Within a given year, the number of active obstetricians is smaller.

Table 1. Descriptive statistics

Sample w/	Unmatched physicians		Matched Physicians			
			All births		Low-risk births	
	Mean	SD	Mean	SD	Mean	SD
Inpatient level variables						
Mother's demographics						
Age	27.740	[5.991]	27.980	[5.973]	27.440	[5.878]
Black	0.198	[0.398]	0.212	[0.408]	0.206	[0.404]
Hispanic	0.216	[0.411]	0.192	[0.394]	0.186	[0.389]
Insurers						
Medicaid	0.496	[0.500]	0.443	[0.497]	0.446	[0.497]
Commercial	0.420	[0.494]	0.477	[0.499]	0.473	[0.499]
No insurance or self-pay	0.050	[0.217]	0.047	[0.211]	0.047	[0.213]
Socio-economic conditions of mother's home zip						
Education (% bachelor)	0.235	[0.118]	0.246	[0.120]	0.246	[0.119]
Median household income (logged)	10.730	[0.301]	10.760	[0.302]	10.760	[0.299]
Risk factors						
Prior C-section	0.200	[0.400]	0.193	[0.395]	\	\
Malposition or malpresentation of fetus	0.046	[0.209]	0.046	[0.210]	\	\
35 years of age or older	0.153	[0.360]	0.160	[0.366]	0.136	[0.343]
Twins or more	0.016	[0.126]	0.017	[0.128]	0.000	[0.00548]
Preterm	0.066	[0.248]	0.068	[0.252]	0.000	[0.00909]
Asthma	0.027	[0.161]	0.027	[0.161]	0.025	[0.156]
Polyhydramnios or oligohydramnios	0.034	[0.180]	0.035	[0.183]	0.033	[0.178]
Physical abnormalities	0.059	[0.235]	0.059	[0.236]	0.046	[0.210]
Blood disorders or issues	0.021	[0.143]	0.022	[0.147]	0.017	[0.128]
Uterine size issues	0.227	[0.419]	0.229	[0.420]	0.230	[0.421]
Infant size issues	0.055	[0.228]	0.060	[0.238]	0.067	[0.251]
Obesity	0.024	[0.154]	0.025	[0.155]	0.020	[0.140]
Anemia	0.084	[0.278]	0.085	[0.278]	0.076	[0.266]
Malnutrition or insufficient prenatal care	0.245	[0.430]	0.247	[0.432]	0.248	[0.432]
Diabetes	0.061	[0.239]	0.062	[0.242]	0.055	[0.228]
Smoking, and alcohol or drug dependence	0.072	[0.258]	0.071	[0.257]	0.069	[0.253]
Infectious and parasitic conditions	0.030	[0.170]	0.031	[0.173]	0.032	[0.176]
Heart diseases	0.010	[0.0985]	0.011	[0.102]	0.010	[0.100]
Fetal abnormality	0.013	[0.112]	0.014	[0.115]	0.012	[0.111]
Antepartum fetal distress	0.003	[0.0555]	0.004	[0.0593]	0.004	[0.0643]
Hypertension	0.083	[0.275]	0.084	[0.277]	0.079	[0.270]
Isoimmunization	0.022	[0.147]	0.025	[0.156]	0.026	[0.158]
Premature rupture of the amniotic sac	0.031	[0.174]	0.031	[0.173]	0.024	[0.152]
Other complications of pregnancy	0.017	[0.128]	0.017	[0.128]	0.016	[0.124]
Low risk	0.708	[0.455]	0.711	[0.453]	\	\
Treatment						
C-section (%)	40.93	[49.17]	40.14	[49.02]	22.69	[41.88]
Unscheduled C-section (%)	9.417	[29.21]	9.225	[28.94]	11.25	[31.60]
	36.64	[48.18]	35.4	[47.82]	17.77	[38.23]
Observations	145,253		187,034		133,009	
Physician level variables						
Female	0.731	[0.444]	0.741	[0.438]		
Tenure (year 2006–graduation year)	18.85	[9.967]	17.83	[8.929]		
C-section rate (%)	41.81	[12.69]	41.5	[11.92]		
Average number of deliveries per quarter	32.32	[23.45]	31.19	[21.55]		
Number of houses (as of 2006/12/31)			1.37	[0.62]		
Residency length (in years, as of 2006/12/31)			4.95	[4.51]		
Purchase price of houses (in 2006 constant $)			552,510.50	[676,454.20]		
Observations	372		487			

Note: This table reports the descriptive statistics for the analytical sample with matched physicians and the leave-out sample where the physicians are not matched. Filters from raw data to these samples are described in Section 4. The sample period is 2007–2009.

5 Methodology

In this section, I first describe how I construct a measure of physicians' housing returns. I then introduce the econometric model and identification strategy.

5.1 Measuring physicians' housing returns

Although CoreLogic has the price of a physician's house at the time of purchase, the market value after the transaction is not known unless there are repeated sales which are infrequent in the data. Therefore, to measure the changes in housing value, I map a time series of the Zillow Home Value Index (ZHVI) to each house based on its zip code.[20] The changes in value a physician perceives from a house located in zip code z is then given by the cumulative housing return since purchase, $R_{z,t} = \frac{ZHVI_{z,t} - ZHVI_{z,t_0}}{ZHVI_{z,t_0}}$. When a physician owns more than one house, I calculated a weighted average cumulative housing return as in Equation 4 below.

$$R_{j,t} = \sum_{z \in \mathbf{Z}_j} w_z R_{z,t} \tag{4}$$

$\mathbf{Z}_j$ is the set of zip codes where physician j has her house(s) in. In implementation, I fix $\mathbf{Z}_j$ at the end of 2006 to avoid distractions by physician's strategic investment/divestment after the crisis began.[21] w_z is the weight of a house in zip code z within the physician's portfolio of houses calculated using inflation-adjusted purchasing price. The more negative (smaller, if positive) $R_{j,t}$ is, the more a physician loses in the value of her house(s).

The same measure in Equation 4 has also been used in the finance and real estate literature. First, it has been shown that the purchase price serves as an important reference point when investors evaluate gains and losses, especially in the real estate market (Tversky and Kahneman, 1991; Genesove and Mayer, 2001). Loss aversion that homeowners exhibit could affect their listing behavior, and in my case, the treatment behavior when they are physicians. Second, Gerardi et al. (2018) and Dimmock et al. (2021) have claimed that the cumulative return predicts how deep underwater the house equity is and therefore the financial distress to a homeowner. In my case, higher financial distress

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

[21] Results are robust to alternative years when the housing portfolios are fixed (e.g., 2007) and time-varying portfolios.

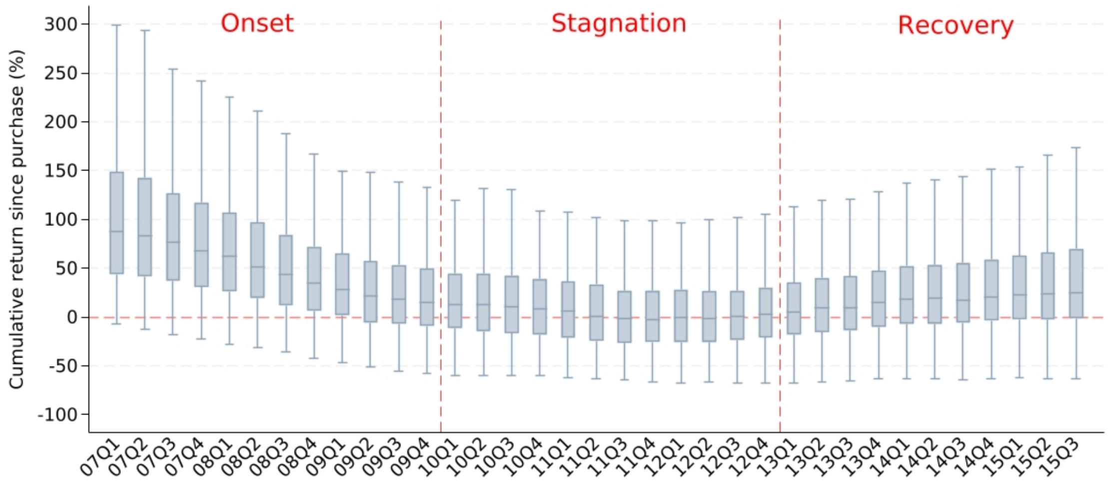
can have an effect on physicians' behavior through higher marginal utility of income. Third, it is also worth noticing that a specification with $R_{j,t}$ as the main independent variable and physician fixed effect is almost equivalent to that using estimating a semi-elasticity of C-section rate with respect to housing value.[22]

The way $R_{j,t}$ is constructed also provides substantial variation for the identification. The trend of declining house prices largely dictates the movement of $R_{j,t}$ on the time dimension. But at a given point of time t, the value of $R_{j,t}$ can vary based on two elements: the zip code z in which physician j resides and the time t_0 when the property is purchased. First, physicians' houses are scattered in different zip codes which tend to exhibit different house price movements even during the same period (Bogin et al., 2019). Appendix figures B2 take four cities in Florida as an example and show that living in different zip codes exposes physicians to different degrees of losses in house value during the crisis. Second, physicians purchase their houses at different times. Figure B3 shows the number of physicians who purchase houses in each year. A good proportion of physicians in the sample purchased their houses in years just leading up to the crisis (i.e., 2004–2006) while many others became house owners in much earlier years. Because of the heterogeneous timing of purchase, even physicians living in the same zip code can experience different levels of loss at a given point in time because they take different price levels as their benchmarks. Figure B4 visualizes this idea by showing the simulated cumulative housing returns had a physician living in an average zip code purchase her house in three different years prior to the recession.

Taken together, Figure 1 summarizes the distribution of this measure at the inpatient level. For an average patient, her attending physician sees almost doubled housing value in the first quarter of 2007 (i.e., the cumulative return since purchase $\approx$ 100%). This premium was gradually eliminated during the prolonged recession. The average physician entered the 2010s with almost zero return. The drop from 100% to 0% captures the negative wealth shock caused by the recession. Throughout the main analysis, I use the onset of crisis (2007–2009) as the sample period. However, my data also covers a period when the real estate market was stagnant (2010–2012) and a period when the market started to rebound and the cumulative housing return increased (2013–2015). It is therefore possible for me to test if positive and negative wealth shocks would have symmetric effects on physician behavior.

[22]Section 7.2 discusses the relationship between the two.

Figure 1. Distribution of physicians' housing returns



5.2 Econometric model and identification

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

$$y_{ijht} = \beta \cdot R_{jt} + \mathbf{X}_i \gamma + \delta_h + \mu_j + \phi_t + \varepsilon_{ijht} \tag{5}$$

where the subscripts i, j, h, and t denote patient, physician, hospital, and year-quarter, respectively. On the left-hand side, y_{ijht} represents the main dependent variable of interest in the case of childbirth, $1\{C - section\}$, a dummy which equals one if the patient receives a C-section and zero if she receives vaginal delivery. Besides this dummy, I also study a number of other margins that an obstetrician can control during the process of childbirth and maternal health outcomes such as length of stay and morbidity. On the right-hand side, R_{jt} captures the physician's housing returns which is defined as in Equation 4. To ease interpretation, I reverse the sign of R_{jt} in the regressions such that an increase in R_{jt} means a loss in wealth (i.e., a negative wealth shock). Therefore, a *positive* estimate of $\hat{\beta}$ would be consistent with the hypothesis that obstetricians respond to negative wealth shocks by performing more C-sections.

In the baseline specification, I additionally control for a battery of patient characteristics, $\mathbf{X}_i$, including (1) demographics such as race, ethnicity, weekend delivery, (2) insurer categories such as dummies for Medicaid, commercial and self-pay/non-insured, (3) socio-economic conditions of mother's home zip code such as education (% with bachelor degree or above) and median household income (logged), and (4) clinical risk factors as measured by comorbidities observed before the onset of labor, such as dummies for prior C-section, advanced maternal age, and etc (reported in Table 1).[23] Importantly, the inclusion of risk factors adjusts for the medical appropriateness of C-section (v.s vaginal delivery) and restricts the test of physician behavior between comparable patients.

I also control for the year-quarter fixed effect to adjust for common time trends and seasonality in physician behavior and wealth shocks. Additionally, to control for provider practice styles that are time-invariant, I include two sets of fixed effects in the baseline specification. The first set is *hospital* fixed effect. Existing papers have revealed a substantial variation in the C-section rate across different facilities (Kozhimannil et al., 2013; Card et al., 2023). If the heavily-shocked physicians happen to work in high- or low-cesarean-rate hospitals, the effect of physicians' wealth shocks would be biased without properly controlling for this difference in hospital practice. The second set of fixed effect is at the *physician* level. Certain obstetricians could be better at performing C-sections or diagnosing patients who are more suitable for C-sections (Epstein and Nicholson, 2009; Currie and MacLeod, 2017). If, for instance, these physicians systematically sort into areas where the house prices decline the most, the wealth sensitivity would be overestimated. Physician fixed effect takes care of this suspicion and other supply-side confounds as long as they do not vary with time at the individual level. Lastly, the combination of physician fixed effect and time fixed effect absorb any time-varying physician characteristics that comove with the linear time trend, such as physician age and work experience (in years).

The identification assumes that which zip code a physician chose to live in and when he bought the house are decisions made before the recession, and therefore uncorrelated with factors that affect her ex-post treatment behavior. Because the housing portfolio is fixed for a given physician, physician fixed effect subsumes the zip code fixed effect and purchase time fixed effect. Therefore, the within-physician variation in housing wealth is mainly driven by the house price movements along the business cycle, and as good as that from randomly exposing physicians to different extents of wealth shocks in a quasi-experiment. While one might suspect that physicians might be aware of the coming crisis and made housing investments strategically, studies such as Cheng et al. (2014) have shown that even financial practitioners couldn't have foreseen the housing bust, let alone medical students and physicians who are reportedly lack of financial literacy (Jayakumar et al., 2017; Igu

[23]Similar risk factors are adopted by previous studies such as Henry et al. (1995), Gregory et al. (2002), Johnson and Rehavi (2016), Currie and MacLeod (2017), and La Forgia (2022).

et al., 2022). The fact that physicians are not clustering in a specific zip code or a specific purchasing time in the data also supports this assumption.

The identification assumption also implies that, after controlling for the aforementioned patient-level covariates, hospital, physician, and year-quarter fixed effects, unobserved determinants of treatment choices are orthogonal to physicians' wealth shocks. As such, any confounds potentially threatening the identification have to be not just correlated with physician wealth shocks but also correlated with it in a time-varying way. Such confounds can arise either from the demand side or from the supply side. On the demand side, I try to include *patient zip code*$\times$*year-quarter* fixed effect, which helps control for patients' riskiness and preferences unobserved to the econometrician. On the supply side, I try to include *hospital*$\times$*year-quarter* fixed effects, which absorb not only hospital-specific practice styles but also any hospital-level incidents such as technology adoption, physician turnover, management reform, etc. Taken together, these extended specifications alleviate the concerns that the effect of physician wealth shocks is in parallel with other channels.

6 Empirical results

6.1 The Effect on C-section rate

6.1.1 Baseline results

This section presents the baseline results for how wealth shocks affect physician behavior. The main outcome variable of interest is a dummy for whether obstetricians perform C-section as opposed to vaginal delivery on a patient, $\mathbf{1}\{C - section\}$. I multiply the dummy by 100 to ease interpretation and run the regressions using linear probability models. Table 2 reports the regression estimates from the baseline specification (Equation 5). All the columns control for patient characteristics, hospital, physician, and year-quarter fixed effects. A positive estimated coefficient before the (reversed) cumulative return implies that greater wealth loss of an obstetrician is associated with a higher probability of C-section, holding all else constant. Take the estimate 2.717 in Column (1) as an example. A one-standard-deviation decrease in physician's housing wealth during the sample period (0.66) leads to an increase of 1.79 percentage points in the C-section rate, which is a 4.5% increase compared to the average (40%). The magnitude of this estimate is non-trivial and explains over 80% of the C-section rate increase in Florida during the period of 2007–2009.

Column (2) of Table 2 repeats the estimation but restricts the sample to *low-risk* births only. Following the guidelines of Agency for Healthcare Research and Quality (AHRQ)[24], low-risk births are defined as those with no indications of prior C-section, hysterotomy, abnormal presentation, preterm delivery, fetal death, multiple gestation diagnoses, or breech birth.[25] Low-risk patients are generally considered good candidates for vaginal delivery and so C-sections are more likely to be unnecessary and motivated by obstetricians' financial incentives. Compared with the estimate in Column (1), the wealth effect on the C-section rate among low-risk births is also significant and even larger in magnitude (3.298). To put it into perspective, a one-standard-deviation decrease in the physician's housing wealth (0.65) leads to an increase of 2.14 percentage points in the C-section rate. Considering that the average C-section rate is smaller among low-risk births (23%), this is equivalent to a 9.4% increase.

Table 2. The effect on C-section rate: Baseline results

	(1)	(2)
Dep. var.	$1\{\text{C-section}\}\times 100$	
Sample	All births (N=187,034)	Low-risk births (N=133,009)
Mean of dep. var. (%)	40.14	22.69
Physician housing return	2.717	3.298
	[0.855]	[1.040]
Patient characteristics	Yes	Yes
Year-quarter FE	Yes	Yes
Hospital FE	Yes	Yes
Physician FE	Yes	Yes

Note: This table reports linear regression results on the C-section rate. The dependent variables are C-section dummy×100. The Independent variables are physicians' housing returns (i.e., reversed cumulative housing return since purchase). The regressions include year-quarter, hospital, and physician fixed effects. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

6.1.2 Orthogonality test

Selection issues can arise in the inpatient-level regression. Specifically, patients of different riskiness and preferences could selectively sort themselves into physicians exposed to different wealth shocks. Alternatively, hard-hit physicians could cherry-pick patients demanding C-sections. It is also possible that hospitals guide patients who are more appropriate for C-sections to obstetricians who

[24]See AHRQ's Inpatient Quality Indicator 33 (IQI 33): https://qualityindicators.ahrq.gov/Downloads/Modules/IQI/V2020/TechSpecs/IQI_33_Primary_Cesarean_Delivery_Rate_Uncomplicated.pdf.

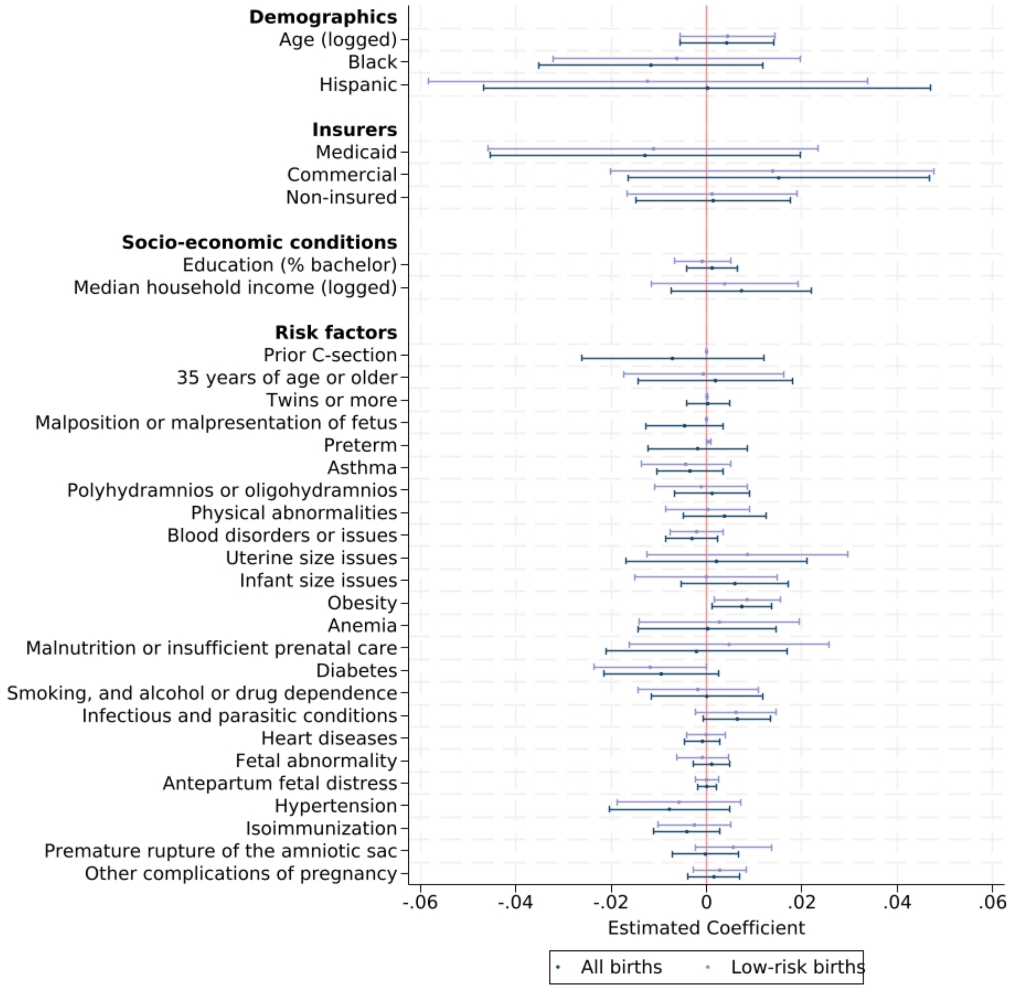
[25]The same criteria of low-risk births is used by La Forgia (2022). I also try an alternative definition of low-risk births using cutoffs based on predicted C-section probability. The results are similar.

experience greater wealth shocks. If such non-random matching between patients and physicians exists, it is difficult to interpret the estimated wealth effect as a causal impact on treatment choices at the intensive margin.

To address this concern, the baseline specification has controlled for a long list of patient demographics and clinical risk factors. In the Appendix, I show that these patient characteristics which an obstetrician observes at the onset of labor can reasonably predict the probability of C-section. In this subsection, I further consider an orthogonality test. Specifically, I regress each of the patient characteristics on physician housing return along with the fixed effects controlled in the baseline specification (i.e., at hospital, physician, and year-quarter levels). Figure 2 shows the estimated coefficients before physician housing return from these individual regressions, for all births and low-risk births separately. Only one of the observed patient risk factors (obesity) can be significantly predicted by physician housing return, suggesting that the patient characteristics are overall "balanced" across time for a given physician.

Finally, I perform a joint F-test by regressing the physician housing return on all the patient characteristics above, along with the fixed effects. The F-statistic is 1.112 with a corresponding p-value of 0.311. I therefore fail to reject the null hypothesis that patients more appropriate for C-sections are paired with physicians with greater wealth shocks. To sum up, it is unlikely that heavily-shocked physicians cream off risky patients based on these observed factors. The detected effect on treatment choices is likely a deviation from the ex-ante behavioral equilibrium given the medical appropriateness, not a shift of the patient profiles.

Figure 2. Orthogonality test



Note: This figure shows the coefficient estimates from individual regressions of patient characteristics on physician housing return. All regressions control for year-quarter, hospital, and physician fixed effects. The sample period is 2007–2009. Confidence intervals are calculated at the 95% significance level.

6.1.3 Extended specifications

Previous sections have shown that selection on the observed patient characteristics is unlikely. However, it remains a question whether patients have unobserved preferences for C-sections, or whether physicians possess and use superior information about their patients that are unknown to the econometricians. For instance, existing studies have revealed that wealth shocks during the recession adversely affect households' physical and mental health outcomes (McInerney et al., 2013; Yilmazer et al., 2015; Fichera and Gathergood, 2016). Patients living in hard-hit zip codes might develop worse conditions, which then justifies the use of C-sections. If these wealth shocks imposed on patients are positively correlated to those of their physicians, the estimated wealth effect could be overestimated.

To alleviate this concern, I control for *patient zip code*×*year-quarter* and *physician*×*patient zip code* fixed effects on top of the baseline regressions. The patient zip code×year-quarter fixed effect absorbs not only the local socio-economic conditions that might affect patients' underlying health (e.g., household income, house prices) but also factors that are difficult to quantify such as preferences for C-sections shaped by community culture and herding behavior. The physician×patient zip code fixed effect helps control for the fact that a physician has her own popular base of patients and word-of-mouth reputation in local communities and so is more likely to attract patients from certain zip codes. Columns (1) and (2) of Table 3 report the estimates with these fixed effects. The fact that they are close to those in Table 2 confirms that unobserved factors on the *demand* side, even though varying by time or by physician, can not explain the changes in physician behavior.

Unobserved confounds could also arise from the *supply* side. For example, hospitals also have financial incentives to encourage C-sections as they receive higher facility fees from the insurers and the fee differential between cesarean and vaginal deliveries might be different for different hospitals Foo et al. (2017). Although the baseline specification has allowed this possibility by including hospital fixed effects, it fails to control for the time-varying aspect as hospitals typically renegotiate with insurers annually. Another example is that hospitals, especially the non-profit ones who invest a good share of their endowments into the stock market, are also exposed to wealth shocks during the same recession (Dranove et al., 2017; Adelino et al., 2022). As a result, hospitals might have extra incentives to promote C-sections just as physicians do. The estimate of the wealth sensitivity could therefore be biased if hospital-level incentives are passed through to physicians. In the extreme, if obstetricians, especially those directly employed by the hospitals, do nothing more than just follow hospitals' guidelines, the estimated effect of physician wealth shocks could merely reflect the effect of hospital wealth shocks.

To deal with this issue, I additionally include *hospital*×*year-quarter* fixed effect on top of the baseline specification (Columns 2 of Table 3). By doing so, I remove the time-series changes in physicians' housing returns that are common for all physicians working in the same hospital at the same time. The coefficient before physician housing return remains statistically significant and in a similar magnitude, showing that physicians' responses to financial incentives are independent of hospitals'.

Finally, the exact value of cumulative housing returns of a physician at a specific time point is partially determined by the purchasing time and it is generally speaking increasing in residency length. In other words, the earlier a physician bought her house, the more likely she maintained a positive house equity despite the crisis. If physicians who settled down earlier (e.g., those who are more senior) gradually become more (or less) willing to perform C-sections over time, the physician fixed effect alone would fall short of correcting this bias. I therefore additionally control for *purchase-year-quarter×focal-year-quarter* FE in Column (4) of Table 3. This effectively restricts the variation in physicians' housing returns to that only induced by physicians residing in different zip codes ex-ante. But even that, the variation is sufficient to deliver qualitatively and quantitatively similar estimates.

Table 3. The effect on C-section rate: Extended specifications

	(1)	(2)	(3)	(4)
Dep. var.	C-section			
Panel A: All births (N=187,034, Mean=40.14%)				
Physician housing return	2.051	2.247	2.231	2.543
	[0.982]	[0.854]	[0.968]	[1.344]
Panel B: Low-risk births (N=133,009, Mean=22.69%)				
Physician housing return	2.739	2.829	3.256	2.321
	[1.204]	[1.054]	[1.180]	[1.598]
Patient characteristics	Yes	Yes	Yes	Yes
Year-quarter FE	Subsumed	Yes	Subsumed	Subsumed
Physician FE	Yes	Subsumed	Yes	Yes
Patient zip code×year-quarter FE	Yes			
Physician×patient zip code FE		Yes		
Hospital×year-quarter FE			Yes	
Purchase-year-quarter×focal-year-quarter FE				Yes

Note: This table reports linear regression results on C-section rate with extended fixed effects. Dependent variable is C-section dummy×100. Independent variable is physician's (reversed) cumulative housing return since purchase. Standard errors clustered at the physician level are in the brackets.

6.2 The effect on other treatment margins

Previous sections have documented the wealth effect on physician behavior and focused on the trade-off between cesarean and vaginal deliveries. In this subsection, I study the effect on other treatment margins that an obstetrician can control. First, I divide C-sections into two types: unscheduled and scheduled. Following Henry et al. (1995), Gregory et al. (2002) and others, unscheduled (scheduled) C-sections are those with (without) ICD diagnosis codes indicating a trial of labor. An obstetrician can advise a scheduled C-section before the due date comes. Among all the cesarean deliveries in Florida, about a quarter are unscheduled. This share is larger among low-risk births (about 50%).

Although it is more likely for high-risk patients to receive a scheduled C-section, the interpretation of medical necessity is subject to an obstetrician's diagnosis. Among all patients who receive scheduled C-sections, about 26% of them are of low risk. If C-sections are not scheduled, patients would enter spontaneous labor and an unscheduled (emergency) C-section could be performed based on uncertainties that appear during the process.

Columns (1) and (2) of Table 4 report results using unscheduled C-section and scheduled C-section dummies as the outcome variable, respectively. Among all births, both unscheduled and scheduled C-section rates change with physician wealth shocks. While among low-risk births, only the unscheduled C-section rate responds. This finding strongly supports the main hypothesis because the use of unscheduled C-sections on low-risk patients is least likely to be driven by medical appropriateness. To put the estimate (2.450) into perspective, physician's wealth decreases by one standard deviation (0.65), unscheduled C-section rate increases by 1.59 percentage points, or 14.2% compared to the mean.

Next, I test if C-sections are performed in combination with ancillary procedures. The ancillary procedures I consider include induction, vacuum, and forceps where induction is used before the labor and vacuum/forceps are used during the delivery (Johnson and Rehavi, 2016). These procedures are used in the hope of helping the labor and avoiding the use of more intensive procedures such as C-sections. Columns (3) and (4) of Table 4 show that only the probability of C-sections without ancillary procedures is significantly increasing in physician wealth shocks. In other words, it is more likely that obstetricians directly resort to C-sections instead of giving other ancillary procedures a try first. This is not surprising as the pay differential between cesarean and vaginal delivery is larger than that between vaginal deliveries with and without ancillary procedures.[26] Use of these ancillary procedures also often requires a longer time and does not guarantee a vaginal delivery in the end, thus further highlighting the attractiveness of a straightaway C-section.

Lastly, I regress logged hospital charges on physicians' housing returns. Hospital charges can be considered as a summary of treatment including the ones specified before (Johnson and Rehavi, 2016). The higher the hospital charges are, the greater the treatment intensity is. Column (5) implies that a one-standard-deviation decrease in physician's housing wealth results in 3.6% increase in hospital charges. This is equivalent to an increase of $468 given the average hospital charges being

[26] To provide some clue, the total hospital charges between cesarean and vaginal delivery are on average $17,252 vs $9,971 while the total hospital charges between vaginal deliveries with and without ancillary procedures is $10,403 vs $9,810.

Table 4. The effect on other treatment margins

	(1)	(2)	(3)	(4)
Dep. var.	C-section			
	Unscheduled	Scheduled	w/o ancillary procedures	w/ ancillary procedures
Panel A: All births (N=187,034)				
Physician wealth shock	1.297	1.420	2.200	0.517
	[0.560]	[0.752]	[0.871]	[0.436]
Mean of dep. var.	9.22	30.92	35.40	4.74
Panel B: Low-risk births (N=133,009)				
Physician wealth shock	2.450	0.847	2.664	0.633
	[0.779]	[0.877]	[1.020]	[0.547]
Mean of dep. var.	11.25	11.44	17.77	4.92
	(5)	(6)	(7)	(8)
Dep. var.	Log(Hospital Charges)			
	Raw	Adjusted	C-section	Vaginal
Panel A: All births (N=187,034)				
Physician wealth shock	0.055	0.040	0.031	0.044
	[0.018]	[0.017]	[0.019]	[0.020]
Mean of dep. var.	9.35	0	9.68	9.12
Panel B: Low-risk births (N=133,009)				
Physician wealth shock	0.061	0.042	0.033	0.044
	[0.020]	[0.019]	[0.022]	[0.020]
Mean of dep. var.	9.25	0	9.74	9.11
Patient characteristics	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes

Note: This table reports linear regression results on other treatment margins. Both cesarean and vaginal deliveries are included in the regressions in Columns (1) to (4). For example, Column (1)'s dependent variable is 100 if the patient receives an unscheduled C-section and 0 if she receives a scheduled C-section or vaginal delivery. A similar definition applies to Columns (2)–(4). Column (6) adjusts for the differences in hospital charges by regressing on the C-section dummy and taking the residuals as the dependent variable. The independent variables are physicians' housing returns (i.e., reversed cumulative housing return since purchase). Other controls are the same as in the baseline specification. Standard errors clustered at the physician level are in the brackets.

$12,894. One might wonder how much of this increase arises from the margin of C-section vs vaginal delivery. I therefore calculate the procedure-adjusted hospital charges by regressing the raw charges on a dummy of C-section. The residual is then used as the dependent variable and regressed on physicians' housing returns. The estimate decreases from 0.055 in Column (5) to 0.040 in Column (6) — a 27.3% decrease — but still remains significant. In other words, the increase in C-section probability for a given patient does not explain all the increase in treatment intensity. In Columns (7) and (8), I further run regressions on subsamples of cesarean and vaginal births separately. Hospital charges for vaginal births also increase in response to physicians' wealth shocks and this increase is even larger than those for cesarean births, indicating obstetricians might also perform more tests/procedures on births that are not appropriate for C-section.[27]

6.3 The effect on patient health

Given the effect of wealth shocks on physician behavior, a natural follow-up question is how this change in physician behavior would affect patients' well-being. On the one hand, the wealth loss motivates physicians to increase treatment intensity more than necessary. This over-treatment deviates from the ex-ante clinical optimum and would probably lead to worse health outcomes. On the other hand, the model predicts that only the marginal patients who are close to being indifferent between cesarean and vaginal deliveries are affected. The empirical estimates suggest that only about 2% of patients are on this margin (Section 6.1.1). The benefits and costs of C-sections on them are less clear. In the end, it remains an empirical question whether there is any meaningful impact on patients' health.

The first measure of maternal health that I examine is the length of stay (i.e., the number of days a patient stays in the hospital from admission to discharge). Intuitively, the increased treatment intensity would also lead to longer length of stay. Estimates of Poisson regression are reported in Column (1) of Table 5 – physician wealth shocks result in longer length of stay. Specifically, a one-standard-deviation decrease in physicians' housing wealth leads to a 0.9% increase in length of stay, or 0.02 days. This is a small increase but largely falls into the same range of estimates in the literature. For example, Card et al. (2023) finds that delivering in a high-cesarean-rate hospital increases the

[27] Note that the regressions have included physician and hospital fixed effects. If I further acknowledge that costs can be different by procedure×physician×hospital (e.g., further controlling for physician×hospital fixed effect in Column (6) of Table 4), such increases in hospital charges would no longer be there.

total length of stay by 0.013 days. Columns (2) and (3) further decompose the length of stay into pre-delivery stay (from admission to delivery) and post-delivery stay (from delivery to discharge). The increase in overall length of stay is mainly driven by an increase in post-delivery stay. These effects on low-risk patients are less significant which echoes the findings in Section 6.2 that even low-risk vaginal births could experience higher treatment intensity.

In-hospital maternal *mortality* are relatively rare. In my data, the maternal mortality during hospital stay is about 4 per 100,000 women. I therefore look at maternal *morbidity*, which is more common during and immediately after the labor and delivery. Following the existing literature (Johnson and Rehavi, 2016; Freedman and Hammarlund, 2019; La Forgia, 2022), I code the following four types of maternal morbidity using ICD-9 diagnosis and procedure codes: hemorrhage, infection, laceration, and other more severe maternal morbidity. The first two types of morbidity, hemorrhage, and infection, are more common in childbirth no matter it is cesarean or vaginal delivery. The third type, laceration, is only present in vaginal delivery and therefore not expected to respond if the C-section rate increases. The last type is less common and includes more severe consequences such as sepsis, eclampsia, anesthesia complications, and others requiring additional procedures including hysterectomy and blood transfusion (Callaghan et al., 2012; Kilpatrick et al., 2016).[28] Overall, more than 5% of all patients in my data developed one or more of these complications.[29]

Columns (4) to (7) of Table 5 report the results of maternal morbidity. Overall, physician wealth shocks result in a slightly higher maternal morbidity rate and this result is mainly driven by the increase in infection. For example, a one-standard-deviation decrease in physician's housing return leads to a 0.25 (0.38) percentage-point increase in the probability of infection among all (low-risk) patients, which is equivalent to a 28% (34%) increase from the mean. This is not an unreasonable magnitude as opposed to some existing estimates in the literature. Although not entirely comparable, Johnson and Rehavi (2016) find that physicians as patients are 26% less likely to have an infection by childbirth, and Freedman and Hammarlund (2019) find that the adoption of electronic medical records helps reduce maternal infection rates in hospitals. Finally, it is consistent with the expectation

[28] For a list of more severe maternal morbidity, see https://www.cdc.gov/reproductivehealth/maternalinfanthealth/smm/severe-morbidity-ICD.htm.

[29] There is a concern that Florida's hospital discharge data could under-report these complications which are slightly lower than those reported in Johnson and Rehavi (2016) using data from California. I also try to study infant morbidity using a similar method. However, it is even more rarely reported in Florida's hospital discharge data. Out of the four commonly studied types (respiratory issues, infection, trauma, meconium), only respiratory-related infant morbidity can be identified and accounts for only 0.05%. I therefore mainly focus on maternal morbidity.

that there is no clear evidence on rates of laceration and severe morbidity being affected as the former is almost specific to vaginal deliveries and the latter is relatively scarce.[30]

Table 5. The effect on maternal health

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Length of stay (unit: days)				Maternal morbidity		
Dep. var.	Total	Pre-delivery	Post-delivery	Hemorrhage	Infection	Laceration	Severe
Panel A: All births (N=187,034)							
Physician wealth shock	0.014	-0.006	0.015	-0.066	0.379	-0.150	0.176
	[0.006]	[0.050]	[0.006]	[0.221]	[0.190]	[0.299]	[0.198]
Mean of dep. var.	2.54	0.29	2.25	1.39	0.97	2.28	0.92
Panel B: Low-risk births (N=133,009)							
Physician wealth shock	0.011	0.002	0.012	-0.325	0.578	-0.153	0.062
	[0.007]	[0.054]	[0.007]	[0.256]	[0.257]	[0.429]	[0.191]
Mean of dep. var.	2.46	0.33	2.12	1.39	1.12	3.06	0.66
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports linear regression results on maternal health. Both cesarean and vaginal deliveries are included in the regressions. Dependent variables in Columns (5)–(7) are multiplied by 100. The independent variables are physicians' housing returns (i.e., reversed cumulative housing return since purchase). Other controls are the same as in the baseline specification. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

6.4 Additional Analyses

6.4.1 Asymmetric responses

So far, the sample period of the main analysis surrounds the onset of the Great Recession (2007–2009). The variation comes from physicians being exposed to wealth loss of different degrees in a quasi-random way. In this subsection, I extend this time frame and include post-crisis periods up to the year 2015. As is mentioned in Section 4, the extended sample includes a period of stagnation (2010–2012) and a period of slow recovery (2013–2015). I run regressions using following the baseline specification for these two extended periods separately.

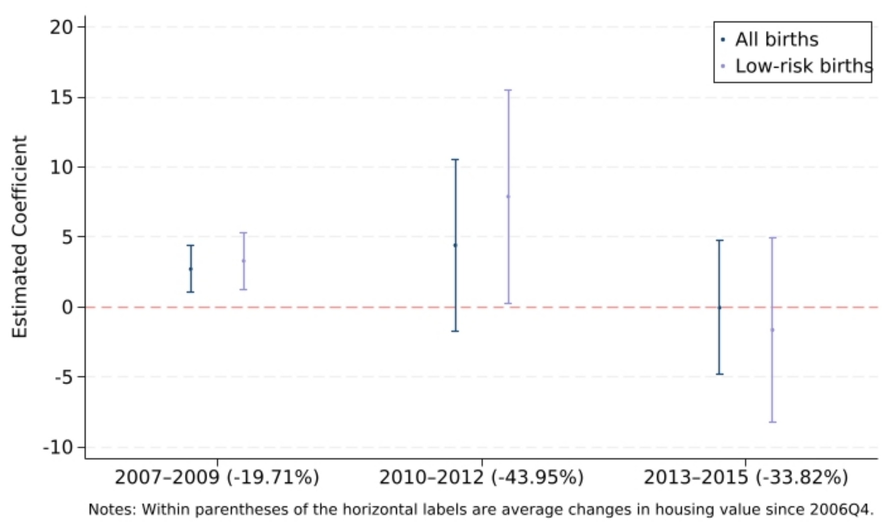
Figure 3 plots the estimated coefficients before the (reversed) physician housing return. Compared to the baseline estimates, obstetricians seem to respond by a greater margin from 2010 to 2012. Note that this is a period when housing prices continue to decline and homeowners are deeper and deeper underwater in their housing equity. An average obstetrician lost around 44% of her housing

[30] The p-values for the estimated increase in infection rate is 0.025 (low-risk births). More conservatively, this result of increased morbidity remains statistically significant at 5% level after Bonferroni correction if I expect three out of four morbidity measures to be affected by physicians' housing returns.

value since the beginning of the crisis. An estimate of a larger magnitude is therefore consistent with the hypothesis. At the same time, it is also worth noticing that physicians are dispersed in heterogeneous zip codes and some of the local markets began to see housing prices rebound during this time period. If physicians do not respond, or respond less, to increasing housing prices (or positive wealth shocks), the wealth effect would be less precisely estimated, which is shown in the figure that the confidence intervals are wider.

Results for 2013–2015 further confirm that physicians do not respond to positive wealth shocks. During this period, housing prices in most of the zip codes have started to increase again. This is reflected by the average loss since 2006 in housing value has shrunk from 44% during 2010–2012 to about 34%. The estimate fails to reject the null hypothesis that obstetricians respond as much as they do to negative wealth shocks. This is consistent with the theory that wealth losses impose more psychological distress than wealth gains of similar size do due to loss aversion (Tversky and Kahneman, 1991), and supported by other empirical evidence that positive wealth shocks do not alter homeowners' behavior (Bernstein et al., 2021; Aslan, 2022).

Figure 3. Extended sample periods



Note: This figure shows corresponding coefficients are from regressions following the same specification as in the baseline (2007–2009) except for extended sample periods (2010–2012 and 2013–2015). Confidence intervals are calculated at the 95% significance level.

Finally, I also provide similar results for the year 2006. Due to data availability, my data only covers one year before the crisis. This test might therefore be underpowered to detect the wealth effect if there is indeed any due to limited within-physician variation in physician housing return. However, it is in line with the findings for 2013–2015 because the housing prices were also increasing in 2006. Table A2 summarizes the results for these extended sample periods. Overall, the wealth effects are concentrated in periods when physicians suffer wealth losses (2007–2012), lending support to my hypothesis.

6.4.2 Heterogeneous effects

Previous sections have documented the average effect of physician housing wealth on treatment intensity. In this subsection, I provide evidence for heterogeneous effects. Specifically, I run regressions following the baseline specification on subsamples divided by patient and physician characteristics and check how the main coefficient of interest varies across these subsamples.

Heterogeneity by patient characteristics

I first provide results by patients' race and ethnicity. Columns (1)–(3) of Table A3 show that black patients are affected the most by physicians' wealth shocks. For example, a one-standard-deviation decrease in physician's housing wealth leads to an increase in C-section rate of 4.3–4.7 percentage points, which is about 2.5 times the average effect. Hispanic patients, on the other hand, are the least affected. Patients who are neither black nor Hispanic are affected by an extent slightly smaller than that of the baseline results.

I then show results by patients' income and education level. Note that I don't observe the exact income and education levels in the data. They are imputed based on patients' zip codes. I divide all the patients into two groups: low-income v.s high-income and low-education v.s high-education. Table A3 shows that high-income patients are more likely to be affected, probably because the insurance that they carry provides more financial incentives for obstetricians. At the same time, low-education patients are more affected, probably because there is a larger information asymmetry between them and their obstetricians, making them more susceptible to exploitation.

Next, I show that the affected patients are more likely to be of medium risk and marginal. Following Currie and MacLeod (2017), I first use all the observed patient risk factors in Table 1 to predict the likelihood of a patient receiving a C-section. The predicted probability is therefore termed the "appropriateness" of a C-section by assuming that, on average, physicians are performing the "correct" amount of C-sections. I then group patients into three categories based on this measure of appropriateness: low, medium, and high. Column (1)–(3) of Table A4 show that the physician wealth effect is the largest among medium-risk patients. Intuitively, it is likely that physicians have already performed C-sections on patients with the highest appropriateness (even without the wealth shocks), and unlikely for them to perform C-sections on patients with the lowest appropriateness (even with the wealth shocks). This is also consistent with the model prediction in Section 3.

Lastly, I show that the wealth effect varies by a patient's insurance type. Columns (4)–(6) of Table A4 show that patients covered by commercial insurance and Medicaid endure the greatest impacts. The same effect is not significant for other patients who are most likely uninsured and thus less profitable from the perspective of physicians. Note that the insurance status could be correlated with other socio-economic factors so these results should not be interpreted as causal evidence.

Heterogeneity by physician characteristics

Table A5 reports results by physician characteristics. Columns (1)–(3) group physicians based on their tenures. For each physician, her tenure is fixed at 2006 (i.e., just before the crisis) and measured as 2006 minus the year she graduated from medical school. The higher a physician's tenure, the longer she has been practicing and the more experienced she is. I find that junior physicians are more responsive to the wealth shocks probably because they have accumulated less wealth but at the same time carried more debt, and so felt the same shock even more. Senior physicians are also sensitive to the wealth shocks, probably because physicians closer to retirement are less worried about the negative impacts of overusing C-sections on their future reputation.

Columns (3) and (4) of Table A5 show that patients attended by female obstetricians are more affected. This result is less intuitive but consistent with what Rizzo and Blumenthal (1994) found among physicians and what Jones and Marinescu (2022) in a more general setting of labor supply. One might also wonder how financial distress affects physicians' responses. Columns (5) and (6) examine how physicians with different home leverage, which I measure using physicians' current Loan-To-Value (LTV) ratio. The LTV is not directly observed from CoreLogic. However, I can impute the current LTV using the initial mortgage amount, mortgage term, and interest rate. I then group physicians into two categories: those above the water (i.e., LTV $<$ 100%) and those underwater (i.e., LTV $\geq$ 100%). The estimated wealth effect is larger in magnitude for the underwater physicians, consistent with findings in the finance literature (Dimmock et al., 2021; Aslan, 2022).

In Table A6, I further test if this wealth effect depends on physicians' ex-ante practice style. Is it that physicians who have already used a lot of C-sections keep pushing the limits, or those who were reluctant to use C-sections now join the crowd? I measure a physician's ex-ante practice style by calculating her C-section rate using 2006's data. This individual-level C-section rate is adjusted for patient risks by subtracting the predicted C-section rate (the same as in calculating the appropriateness) from the actual C-section rate. A physician with a high risk-adjusted C-section rate is therefore performing C-sections despite clinically unjustified. Columns (1) and (2) of Table A6 show that physicians who do more C-sections ex-ante are either willing and capable of doing even more when faced with negative wealth shocks.

Lastly, I test if physician competition would moderate the wealth effect. The hypothesis is that physicians are only capable of responding to wealth shocks if they have market power and do not need to worry about the "demand punishment". To measure physician competition, I use two proxies. The first one is density defined as the number of physicians per patient in a local market. The more physicians a patient can choose from, the more competitive a local market is. The second proxy is the Herfindahl-Hirschman Index (HHI) calculated using physician-level market shares of patients. The higher HHI is, the less competitive a local market is. I then define a market as a "less competitive" one if its density is smaller than the median and its HHI is larger than the median. Similarly, "more competitive" markets are those with density larger than the median and HHI smaller than the median. I also try to define a local market as a zip code or a county. Columns (3)–(6) consistently show that physicians only respond by doing more C-sections in less competitive markets. This result complements the finding in (Ikegami et al., 2021) and provides a more complete picture of how competition might shape physician-induced demand.

6.5 Robustness checks

Alternative specifications

All the main results involving dummy dependent variables are estimated using a linear probability model. I show in Table A7 that results are similar using a non-linear probability model such as logit. Also, all the regressions in the main results cluster standard errors at the physician level. I show in Table A8 that results remain similar if the standard errors are clustered at alternative levels such as hospital, patient zip code, and physician zip code.

Alternative measures

I then test if the results are insensitive to how the physician housing return is constructed. In Table A9, I consider alternative measures including (1) cumulative housing return measured against the maximum value for each physician, (2) cumulative housing return measured against the value as of 2006Q4, (3) cumulative housing return since purchase but allowing physicians' housing portfolios to be time-varying, and (4) cumulative housing return since purchase but lagged one quarter.

The first two alternative measures impose the same value of wealth shocks at a given point in time to physicians living in the same zip code. In other words, the within-physician variation of wealth shocks no longer depends on the time when physicians purchase the houses. Still, the estimates uncover a significant relationship between wealth shocks and the use of C-sections. Moreover, the portfolios are fixed by what they were at the end of 2006 in the main analysis. The third alternative measure relaxes this constraint and allows the portfolios to be time-varying as they could be in reality. Physicians could buy or sell their houses in response to the wealth shocks that they experienced. Such actions reset the subsequent perceived wealth shocks and at the same time might affect her working routine (e.g., how far she is away from her patients, how much time he spends on commute and patient care, etc). However, the main results are insensitive to this alternative construction. One also might wonder if physicians would respond to the wealth shocks instantaneously. The last alternative measure of housing return uses wealth shocks in the last period to predict the treatment in the current period. The significant results indicate that physicians' responses do not have to be immediate.

Allowing physician turnover

In the main analysis, I focus on obstetricians who keep seeing patients from 2006 to 2010, covering the sample period of 2007–2009. In Table A10, I relax this restriction and allow physician turnover. Specifically, I include obstetricians who only entered the labor force after the recession began (i.e., late entries) and those who retired before the recession ended (i.e., early exits). These obstetricians could have different objectives and attitudes towards risks at the early or late stage of their careers. However, the main results remain the same with them in the sample.

7 Discussion

The main empirical finding in previous sections is that negative wealth shocks lead to physicians adopting more profitable treatment choices, all else constant. In this section, I first use a simple model to derive the Slutsky Equation where the effect of physician fees on treatment choices can be expressed as a sum of the wealth effect and the substitution effect. I then show how the model predicts the treatment choices under two counterfactuals: (1) an "across-the-board" fee cut as a form of price regulation, and (2) a transition from the Fee-For-Service schedule to the capitation model.

7.1 A model of treatment choices

Section 3 has outlined a conceptual framework where an obstetrician makes a *discrete* choice of cesarean or vaginal delivery. Here, I consider a *continuous* version of the same model which is similar to a typical labor supply model except I model labor supply as the probability of a physician adopting the more profitable treatment (i.e., the C-section rate), and model wage rate as the pay differential between cesarean and vaginal deliveries. The physician obtains utility from income (and then consumption as in a standard labor supply model) and disutility from performing too many C-sections (and therefore potentially harming patients' health). Specifically, the physician's utility function is given by:

$$\begin{aligned} \text{Max:} \quad & U(Y, I) = U(Y) + U(G) \\ \text{where} \quad & Y = [w_c \cdot p + w_v \cdot (1-p)] \cdot N + H \\ & G = N \cdot p \end{aligned} \tag{6}$$

where p is the C-section rate; w_c and w_v are physician fees for cesarean and vaginal deliveries, respectively. The total number of deliveries is denoted as N and exogenous over a given period of time.[31] Y is the obstetrician's total income including professional earnings, $[w_c \cdot p + w_v \cdot (1-p)] \cdot N$, and housing return, H. Further, let $w \equiv w_c - w_v > 0$ denote the pay differential between cesarean and vaginal deliveries.[32] It is assumed that $U_Y > 0$. G is the number of cesarean deliveries performed. The more C-sections that an obstetrician performs, the more likely her patients whom she cares about

[31] A physician-level regression with physician- and time-fixed effects has confirmed that the number of deliveries does not respond to physicians' wealth shocks.

[32] The costs of performing C-sections and vaginal deliveries can be different. One should think of w_c and w_v as cost-adjusted so they represent the raw benefits to the physicians. The assumption is that C-sections are reimbursing more than vaginal deliveries even accounting for costs. I have discussed this in Section 2.

receive unnecessary treatment.[33] In other words, $U_G < 0$. This is consistent with the models of physician-induced demand in the literature (McGuire and Pauly, 1991; Gruber and Owings, 1996; Gruber et al., 1999; McGuire, 2000) that physicians incur conscientious costs from inducing too much. Finally, $U_{YY} < 0, U_{GG} < 0$. The obstetrician chooses p to maximize utility. The first order condition is given by:

$$(w_c - w_v) \cdot U_Y = -U_G \tag{7}$$

which says the marginal pecuniary benefit of performing a C-section must equal the marginal conscientious cost. By fully differentiating Equation 7 above with respect to w_c and w_v, I can derive the marginal effects of physician fees on the C-section rate:

$$\begin{aligned}\frac{dp}{dw_c} &= -\frac{U_Y}{N \cdot U_{GG}} + \frac{-w \cdot U_{YY}}{N \cdot U_{GG}} \cdot N \cdot p \\ \frac{dp}{dw_v} &= \frac{U_Y}{N \cdot U_{GG}} + \frac{-w \cdot U_{YY}}{N \cdot U_{GG}} \cdot N \cdot (1-p)\end{aligned} \tag{8}$$

It can be shown that change in C-section rate p due to changes in physician fees $\triangle w_c$ and $\triangle w_v$ is a combination of the substitution effect and the wealth effect (Equation 9). My empirical estimate is exactly the wealth effect except for not yet scaled by the change in overall income.[34]

$$\begin{aligned}\triangle p &= \frac{dp}{dw_c} \cdot \triangle w_c + \frac{dp}{dw_v} \cdot \triangle w_v \\ &= \underbrace{\frac{-U_Y}{N \cdot U_{GG}}(\triangle w_c - \triangle w_v)}_{\text{Substitution Effect}} + \underbrace{\frac{-w \cdot U_{YY}}{N \cdot U_{GG}} \cdot N \cdot [p \cdot \triangle w_c + (1-p) \cdot \triangle w_v]}_{\text{Wealth Effect}} \\ &= \underbrace{\overbrace{\frac{-U_Y}{N \cdot U_{GG}}}^{>0}(\triangle w_c - \triangle w_v)}_{\text{Substitution Effect}} + \underbrace{\overbrace{\frac{dp}{dH}}^{<0} \cdot N \cdot [p \cdot \triangle w_c + (1-p) \cdot \triangle w_v]}_{\text{Wealth Effect}}\end{aligned} \tag{9}$$

Equation 9 is the Slutsky Decomposition which states that the *net* marginal effect of changes in $\triangle w_c$ and $\triangle w_v$ can be decomposed into two counter forces. The *substitution effect* is the change in C-section rate due to changes in the relative attractiveness of cesarean and vaginal deliveries from the obstetrician's point of view while holding the wealth level constant. In other words, the substitution

[33] In reality, physicians may feel guilty only after the C-section rate goes over a certain threshold or deviates from the clinical optimum. For example, $U(G)$ is decreasing in $G - \tilde{G}$. This nuance is abstracted in the functional form of $U(G)$ and should not affect the model prediction.

[34] To see this, fully differentiate Equation 7 with respect to H and it gives $\frac{dp}{dH} = \frac{-w \cdot U_{YY}}{N \cdot U_{GG}}$.

effect is income-compensated and always leads to a lower C-section rate as long as a combination of $\triangle w_c$ and $\triangle w_v$ results in a smaller pay differential, w. On the other hand, the *wealth effect*, captures the change in C-section rate when fixing the relative wage rate of cesarean and vaginal deliveries but perturbing the wealth level. This effect leads to a higher C-section rate as long as $p \cdot \triangle w_c + (1-p) \cdot \triangle w_v$ is negative. Consistent with the previous discussion, the key to this result is the concavity of $U(Y)$ (i.e., $U_{YY} < 0$ in the numerator). The *net effect* is ultimately determined by which effect dominates the other and how the changes in $\triangle w_c$ and $\triangle w_v$ are structured. For example, if the wealth effect is strong enough to offset the substitution effect, a lower w would increase p, which gives rise to an analogue of the so-called "backward-bending" labor supply curve.[35]

Further, one can derive the change in expenditure on physician fees:

$$
\begin{aligned}
\triangle C &= \big[w_c' \cdot p' + w_v \cdot (1-p')\big] \cdot N - \big[w_c \cdot p + w_v \cdot (1-p)\big] \cdot N \\
&= \underbrace{[\triangle w_c \cdot p + \triangle w_v \cdot (1-p)] \cdot N}_{\text{savings w/o physician response}} \quad + \quad \underbrace{(w_c - w_v) \cdot \triangle p \cdot N}_{\text{savings offset by physician response}}
\end{aligned}
\tag{10}
$$

7.2 Policy implications

Under the current healthcare system in which physicians' financial incentives are closely related to physician fees, price regulation remains an important policy tool in moderating healthcare provision and medical expenditure. I first show the importance of the wealth effect in determining the effectiveness of price regulation by considering an "across-the-board" fee cut. In this counterfactual, changes in physician fees are the same for different procedures and the change in treatment choices is solely driven by the wealth effect. I then illustrate the importance of the substitution effect through a second counterfactual. In this counterfactual, physician fees change such that the pay differential between different treatments is eliminated while physicians' earnings are made unchanged. Therefore, the change in treatment choices is solely driven by the substitution effect.

In the setting of labor and delivery, proposals to decrease the C-section rate include advocates for a smaller pay differential between C-section and vaginal delivery. Although there are existing studies in the literature that directly estimate the effect of smaller pay differential on C-section rate,

[35]In a typical labor supply model where the agent trades off between consumption and leisure, the Slutsky Equation states that $\frac{\partial L}{\partial w}\Big|_{uc} = \frac{\partial L}{\partial w}\Big|_{c} + \frac{\partial L}{\partial I} \cdot L$ where L is the labor supply (e.g., the hours worked), w is the wage rate, and I is the income. $\frac{\partial L}{\partial w}\Big|_{uc}$ is the uncompensated price effect (or the effect on Marshallian labor supply). $\frac{\partial L}{\partial w}\Big|_{c}$ is the compensated price effect (or the substitution effect), and $\frac{\partial L}{\partial I} \cdot L$ is the wealth effect, scaled by the work amount.

these *raw* estimates are less useful in scenarios where out-of-sample predictions hinge on factors such as how the reduced pay differential is achieved and how much a physician's income is affected by the changing fee schedule. For example, decreasing the fees for C-section (i.e., a negative earning shock for obstetricians) could have dramatically different implications than increasing the fees for vaginal delivery by the same amount (i.e., a positive earning shock for obstetricians). Also, a decrease in fees for C-sections could mean very differently between obstetricians who perform relatively more C-sections (and thus feel the negative income shock more) and those who perform relatively fewer C-sections (and thus the earning reduction does not hurt as much). From Equation 9, one can see that, other than $\frac{dp}{dH}$ which is something I estimate, how a fee change plays out through the wealth effect also depends on N, p, $\triangle w_c$, and $\triangle w_v$.

The semi-elasticity of C-section rate with respect to wealth

The main results use physicians' housing returns as the main independent variable. To perform policy counterfactual, I will have to estimate the marginal wealth effect (i.e., $\frac{dp}{dH}$). In practice, physicians' wealth levels can be skewed and so the estimate of $\frac{dp}{dH}$ can be sensitive to extreme values. I therefore use the logged housing value as the independent variable and estimate the semi-elasticity of the C-section rate. Housing value is estimated using the (inflation-adjusted) purchase price of a house multiplied by the cumulative house price growth. Therefore, this specification should deliver qualitatively the same results as the baseline specification.[36] The identification utilizes the within-physician variation in housing value which is dependent on which zip code a physician lives in and most plausibly exogenous.

Table A11 reports the result with *log(housing value)* as the explanatory variable. Take the result for low-risk births in Column (1) as an example. A 10% decrease in physicians' housing wealth leads to an increase of 0.69 percentage points in the probability of C-section for an average patient. To translate this semi-elasticity w.r.t housing value into semi-elasticity w.r.t total personal wealth, one needs to know the following two things: how much leverage a house takes and how much housing wealth accounts for a physician's total wealth. First, I calculate the Loan-To-Value (LTV) ratio using mortgage information in CoreLogic. The median LTV among in my sample is 40%, meaning that

[36] To see this, notice that in the specification $y_{jt} = \phi \cdot log(P_{jt}) + \delta_j + \varepsilon_{jt}$, ϕ is the semi-elasticity of y with respect to housing value P. And $log(P_{jt}) = log\big(P_{j0} \times (R_{jt} + 1)\big)$ can be approximated by $log(P_{j0}) + R_{jt}$ where $log(P_{j0})$ is absorbed by the fixed effect δ_j.

housing equity is about 60% of the housing value. Second, it is estimated housing wealth accounts for about 20% of a physician's total wealth (Survey of Consumer Finance, 2009). Taking these two ratios into account, the decline in housing value for an average physician during the financial crisis (-20%, 2007–2009) is equivalent to a 6.6%($= 20\% \times \frac{20\%}{1-40\%}$) decline in her net wealth, which constitutes a non-trivial wealth shock. Finally, using the same conversion, I estimate that *a 1% decrease in physicians' total wealth leads to a 0.21 percentage point increase in the C-section rate*.

Counterfactual 1: Across-the-board fee cut

The first counterfactual is an "across-the-board" fee cut under the Fee-For-Service scheme. In this scenario, physician fees are lowered by the same amount for both C-section and vaginal delivery. By cutting fees by the same degree for different physician services, policymakers may hope to maintain the treatment intensity while only changing the prices. Although it has been acknowledged that physicians might respond to such fee cuts at least at an extensive margin (e.g., by working more hours and providing more services), responses at the intensive margin are not often discussed. The setting of labor and delivery provides an ideal laboratory for studying this issue. Intuitively, this type of fee cut shuts down the substitution effect by setting $\triangle w_c - \triangle w_v = 0$. However, $\triangle w_c$ and $\triangle w_v$ both being negative means that earnings are lower for physicians. As a result of the wealth effect, physicians are more likely to adopt the more profitable option (i.e., C-section), thus increasing the treatment intensity at the intensive margin.

Such price regulations are probably a blunt way to reduce medical expenditure. However, it is not uncommon in a policymaker' toolkit. Although not in the setting of labor and delivery, an example of such "across-the-board" price changes is the annual update of Medicare's physician fee schedule which follows a Sustainable Growth Rate (SGR) formula. Put in place through the Balance Act of 1997, the SGR is a system designed to control the spending on Medicare's payment for physician services. Under the SGR system, if expenditures over a period are less than the cumulative spending target for the period, the physician fees would be updated upwards for the next year. On the contrary, if spending exceeds the target, future updates are reduced to bring spending back in line with the target (Hahn and Mulvey, 2010). The target rate is closely related to the per-capita GDP growth rate and so when the economic growth slowed at the turn of the century, the SGR formula triggered a mandated "across-the-board" fee cut of 4.8% in 2002. Since then, the gap between actual and target expenditures widened and Congress had to step in with short-term legislation (i.e., the so-called "doc fix") to avert the SGR-mandated cut and keep the payment level unchanged or slightly increased. In 2015, the SGR formula would dictate a 21.2% cut in physician fees had Congress failed to override it (Reschovsky et al., 2015).[37]

Table 6 calculates the changes in the C-section rate under different across-the-board fee cuts. Take the fee cut that was actually triggered in the year 2002 as an example. Physicians would respond to the lower earnings and increase the C-section rate by 0.81 percentage points. This increase in the C-section rate is linear in the size of the fee cut. For the one proposed in 2015 (–21.2%), the C-section rate is predicted to be 3.56 percentage points higher. Note that the real-life "across-the-board" fee cuts are often time designed as price reductions by a certain percentage, instead of by certain dollar amounts. But even that, the $\triangle w = \triangle w_c - \triangle w_v$ in Equation 9 would be very small. For example, a 10% fee cut conditional on a \$100 ex-ante pay differential could only generate a $\triangle w$=\$10 which then results in an almost negligible substitution effect. Therefore, my model, even though parsimonious, can provide a reasonable approximation if either the percentage fee cut or the ex-ante pay differential is small.

Equation 10 says that the proportion of cost savings offset by the increased C-section rate depends on the ex-ante pay differential between C-section and vaginal delivery. Here, I calibrate the ex-ante physician fees for cesarean and vaginal deliveries as \$3,350 and \$2,887 using estimates in (Corry et al., 2013).[38] In other words, the average pay differential is $w = \$3,350 - \$2,887 = \$463$. Column (3) and (4) in Table 6 report the cost savings that are offset by the increased C-section rate in dollars. For a 10% "across-the-board" fee cut, cost savings are offset by about 7.8 dollars per delivery and about 31.12 million dollars per year. Such a "volume-offset" effect highlights the unintended consequences of "across-the-board" fee cuts and confirms the concern of the Congressional Budget Office which predicts the changes in future spending from annual updates of physician fees (Congressional Budget Office, 2007).

In reality, there are several points that one should keep in mind about this effect. First, how much the wealth effect would increase the C-section rate and compromise the realized cost savings depends

[37]The temporary SGR overrides have produced contentious political battles over how to pay for them. In April 2015, President Barack Obama signed the Medicare Access and CHIP Reauthorization Act of 2015 into law and permanently repealed the SGR.

[38]These are the average professional fees on the delivery and the postpartum care calculated using claims data of MarketScan from 2004 from 2010 at the national level.

on the ex-ante pay differential. In markets with larger pay differential, the wealth effect could induce larger responses. Second, the offsetting effect I find here is only at the intensive margin. On top of this, physicians could respond to fee cuts by providing more services in the aggregate. How the offset at the extensive margin is compared to that at the intensive margin and to the benchmark cost savings is beyond the scope of this paper.

Table 6. Counterfactual 1: Across-the-board fee cuts

(1) Across-the-board fee cuts	(2) Changes in C-section rate	(3) Cost savings offset by the increased C-section rate per baby	(4) Cost savings offset by the increased C-section rate per year
-4.8% (the cut triggered in 2002)	0.81 p.p.	\$3.73	\$14.92M
-10%	1.68 p.p.	\$7.78	\$31.12M
-21.2% (the cut proposed in 2015)	3.56 p.p.	\$16.49	\$65.96M

Note: The ratio of professional earnings to total income is estimated to be 80% for an average obstetrician in Florida using data from Gottlieb et al. (2020). The ex-ante pay differential between C-section and vaginal delivery is set to be \$463 as in Corry et al. (2013). The number of baby deliveries per year is assumed to be 4 million.

Counterfactual 2: Transition from FFS to capitation

In this counterfactual, I consider the transition from the Fee-For-Service scheme into alternative payment models where financial incentives arising from different physician fees across services are reduced or eliminated. An example of such models is vertical integration where physicians are directly employed by the hospitals and paid a fixed amount of salary. Diminished financial incentives to physicians are shown to be crucial in understanding the impact of vertical integration on physician behavior (Lin et al., 2013; Saghafian et al., 2023).[39] Another example is bundled payment which has been proposed in the hope of cutting costs and improving patient outcomes in maternity care.[40] In a bundled payment plan, the insurer pays physicians with a lump sum for care provided within an episode of care (e.g., from delivery to 60 days afterward). Obstetricians receive the same amount of remuneration no matter whether the cesarean or vaginal delivery is performed. Below, I call these alternative models which pay the obstetricians regardless of the delivery method *capitation* payment in the sense that how much an obstetrician earns from delivering a baby is fixed ex-ante.

How does transition into a capitation model affect physician behavior? It is expected that the

[39] However, there could be financial incentives at the hospital level and hospitals might be able to pass such incentives to the employed physicians through ways other than fixed-rate contracts such as bonuses.

[40] See media coverage such as https://kffhealthnews.org/news/maternity-care-bundling-payments-insurance-cesarean-sections/, and policy report such as https://www.macpac.gov/wp-content/uploads/2021/09/Value-Based-Payment-for-Maternity-Care-in-Medicaid-Findings-from-Five-States.pdf.

C-section rate would be lower since the channel of financial incentives is (at least mostly) shut down. But how much lower is the new C-section rate? First, I consider a fiscally neutral case where the capitation policy sets a single flat fee equal to the ex-ante expected expenditure for an average birth. In this case, the wealth effect is muted as the obstetricians get paid the same on average so the change in C-section rate is solely driven by the substitution effect (i.e., perfect income compensation). Therefore, knowing the sign and size of the substitution effect is important in making the prediction.

Having an estimate of the wealth effect enables me to back out the substitution effect using the Slutsky Equation. Intuitively, the substitution effect is just the net effect minus the wealth effect. However, there are neither physician charges/allowed amounts in my data nor exogenous changes in physician fees during the sample period that I can use to credibly estimate the net effect on my own. Instead, I source the estimated net effect from previous studies in the literature. There are three notable references in this setting. Gruber et al. (1999) use within-state over-time variation in Medicaid's pay differential between cesarean and vaginal deliveries (1988–1992), and estimate that a \$100 increase in fee differential leads to a 0.7 percentage point rise in C-section rate. Using a similar empirical strategy but more recent state-level Medicaid data (1990–2008), Alexander (2017) estimates that the C-section rate increases by 0.6 percentage points as the pay differential increases by \$100. Foo et al. (2017) measure pay differential using data from private insurers (2004–2011, California). Their estimate indicates that a \$100 increase in pay differential can result in a 0.6 percentage point increase in C-section rate.[41] Overall, these estimates are not far away from each other. For the sake of simplicity, I adopt Foo et al. (2017)'s estimate and assume the net effect as such that *a \$100 decrease in the pay differential corresponds to 0.6 percentage point decrease in the C-section rate*.[42]

Note that the existing estimate of net effect is only with respect to the pay differential (w), instead of with respect to single fees (w_c or w_v). In practice, however, there could be more than one way to arrive at a smaller pay differential with the combination of single fees. For example, for a \$100 decrease in w, one can either lower the w_c by \$100 (while holding the w_v fixed), or increase the w_v (while holding the w_c fixed), or lower the w_c and w_v at the same time. Lowering the w_c leads to lower per-birth earnings for the obstetricians. The C-section rate would increase due to the wealth

[41] Their result states that a \$100 increase in the pay differential leads to a 2.7 increase in the logged odds ratio. This is equivalent to a 0.6 percentage point increase in the C-section rate, given that odds ratio= $\frac{p}{1-p}$ and the average C-section rate in their sample is 0.29.

[42] Note that Medicaid's fee differential is zero in Florida and so it is reasonable to put more weight on Foo et al. (2017)'s estimate than on Gruber et al. (1999) and Alexander (2017)'s.

effect. On the contrary, increasing the w_v implies higher per-birth earnings for the obstetricians, and bringing down the C-section rate even further. Any other combination of $\triangle w_c$ or $\triangle w_v$ would have implications for obstetricians' earnings in between these two extreme cases. Therefore, using Equation 9, I can recover an interval for the substitution effect:

$$\text{N.E.} - \underbrace{\frac{dp}{dH} \cdot N \cdot p \cdot \triangle w_c}_{\text{W.E. of a decrease in } w_c} \leq \quad \text{S.E.} \quad \leq \text{N.E.} - \underbrace{\frac{dp}{dH} \cdot N \cdot (1-p) \cdot \triangle w_v}_{\text{W.E. of a increase in } w_v} \tag{11}$$

I back out the substitution effect in the context of California. For simplicity, I consider the case where the reduction of pay differential is achieved only by lowering the w_c. In this special case, the substitution effect is just N.E. $- \frac{dp}{dH} \cdot N \cdot p \cdot \triangle w_c$. I use calibrated parameters from Foo et al. (2017). Specifically, the average C-section rate is 29% and the average physician fee is about $2,434.[43] I also rely on Gottlieb et al. (2020) which discovers that the percentage of patient-care earnings in a California's physician's total income is about 73%. In the end, the recovered substitution effect is about -0.78 p.p. for a $100 decrease in pay differential. In terms of magnitude, the wealth effect offsets about 23% ($= \frac{-0.78+0.6}{-0.78}$) of the substitution effect.[44] Table 7 summarizes the calculation.

Table 7. The Slutsky Decomposition

Parameters	
A1: Semi-elasticity of C-section rate w.r.t total wealth	–0.21 p.p.
A2: Average C-section rate	29%†
A3: Average professional earnings from labor and delivery	$2,434†
A4: Income from labor and delivery/total income	73%‡
Changes in pay differential	**–$100**
Changes in C-section rate	
Net effect	**–0.6 p.p.**
Wealth effect	$A1 \times \frac{-\$100 \times A2}{A3/A4 \times 1\%}$ = **0.18 p.p.**
Substitution effect	–0.6 p.p. – 0.18 p.p. = **–0.78 p.p.**

Notes: Parameters are sourced from the literature: † Foo et al. (2017); ‡ Gottlieb et al. (2020).

As a result, transitioning from the Fee-For-Service to the capitation (i.e., closing the pay differential) would lower the C-section rate by at most 1.76 percentage points, conditional on the pay

[43] I use the average cesarean rate and the median physician fees for cesarean/vaginal births from 2007 to 2009 in Table 2.

[44] Note that –0.78 p.p. is an upper bound (in terms of magnitude) of the substitution effect. Following Equation 11, the full range of the substitution effect is [–0.78, –0.15] p.p. On average, the substitution effect is such that a $100 decrease in the pay differential corresponds to a 0.465 percentage point decrease in the C-section rate.

differential being $225 as in Foo et al. (2017). This is a decrease of 6.1% compared to the average level of 29% in California. In reality, capitation plans usually hold physicians accountable for the quality of care by providing bonuses/punishments if certain criteria are hit/missed. This creates financial risks for the physicians, leading to even lower provision of C-sections (Aizer et al., 2007; Kuziemko et al., 2018). In that sense, my estimate only provides a lower bound of the actual decrease in the C-section rate under the capitation model. My estimate is also comparable to those in similar studies. For example, Rosenstein et al. (2021) find that the C-section rate in California decreased by 3.2 p.p. from 2014 to 2019 because of a series of initiatives including payment reforms, data transparency, patient engagement, and etc. McNamara and Serna (2023) find that the C-section rate in California could be reduced by 2.6 p.p. if the payment contracts between hospitals and insurers change from Fee-For-Service to capitation. My study shows that reducing the financial incentives at the physician level alone could also generate sizable progress in addressing the overuse of C-sections.

8 Conclusions

This paper empirically estimates the sensitivity of physicians' behavior to their personal wealth and studies the policy implications of this sensitivity on medical expenditure and patient health. In doing this, I take advantage of a unique data set linking physicians' housing returns to their treatment choices, and leverage quasi-experimental variation in housing returns created by the Great Recession. My fixed-effect estimate suggests that physicians respond to negative wealth shocks by adopting the more profitable treatment at the intensive margin — patients are more likely to receive C-sections other than vaginal delivery, all else constant. As a result, patient health becomes worse off, reflected by longer length of stays and higher maternal infection rates.

I then use a simple model to illustrate that physicians' sensitivity to wealth can be closely related to the price effect through the Slutsky Equation with substitution effect and wealth effect. Using two counterfactuals, I show that my estimate is useful in making out-of-sample predictions of how price regulations and alternative payment models can affect medical expenditure and the C-section rate. Because of the wealth effect, an "across-the-board" reduction in physician fees could have an unexpected effect by increasing the C-section rate and compromising the proposed cost savings. Ignoring the wealth effect could also underestimate the decrease in the C-section rate if the payment structure transitions from Fee-For-Service to capitation.

The high C-section rate has been a public health concern in the United States. An important policy interest in reducing the C-section rate is through physician payment reforms.[45] My results speak directly to the impacts of some of these proposals by highlighting the side effects of universal fee cuts and the potentials of capitation models. This paper also calls for attention to factors that are out of the healthcare system but can also affect physician behavior. Personal wealth shock is just one such incident. It is also worth noticing that real estate shock is just one of the many sources of wealth shock. Other possible sources can come from the stock market, residential mortgages, and student loans, all of which physicians have heavy footprints on. Future research can therefore exploit exogenous variations in these settings to identify the effect on physician behavior.

[45] For example, https://www.macpac.gov/wp-content/uploads/2019/04/Medicaid-Payment-Initiatives-to-Improve-Maternal-and-Birth-Outcomes.pdf.

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Appendices

A Additional figures and tables

Figure A1. **Trends of childbirth and C-section in Florida**

Note: This figure shows the evolution of C-section rates in Florida from 2006 to 2014, calculated using data from the Florida Agency for Health Care Administration. Low-risk births are defined as those with no indications of prior C-section, hysterotomy, abnormal presentation, preterm delivery, fetal death, multiple gestation diagnoses, or breech birth.

Table A1. Orthogonality test

		All births		low-risk births	
		coef	*s.e.*	*coef*	*s.e.*
Mother"s demographics	Age (logged)	0.004	0.005	0.005	0.005
	Black	-0.012	0.012	-0.006	0.013
	Hispanic	0.000	0.024	-0.012	0.023
Insurers	Medicaid	-0.013	0.016	-0.011	0.018
	Commerical	0.015	0.016	0.014	0.017
	No insurance or self-pay	0.002	0.008	0.001	0.009
Socio-economic conditions	Education (% bachelor)	0.001	0.003	-0.001	0.003
of mother"s home zip	Median household income (logged)	0.008	0.007	0.004	0.008
Risk Factors	Prior C-section	-0.009	0.010	0.000	0.000
	35 years of age or older	0.001	0.008	-0.001	0.009
	Twins or more	0.001	0.002	0.000	0.000
	Malposition or malpresentation of fetus	-0.004	0.004	0.000	0.000
	Preterm	-0.002	0.005	0.000	0.000
	Asthma	-0.003	0.004	-0.004	0.005
	Polyhydramnios or oligohydramnios	0.001	0.004	-0.001	0.005
	Physical abnormalities	0.003	0.004	0.000	0.004
	Blood disorders or issues	-0.004	0.003	-0.002	0.003
	Uterine size issues	0.002	0.010	0.009	0.011
	Infant size issues	0.006	0.006	0.000	0.008
	Obesity	0.007	0.003	0.008	0.004
	Anemia	-0.001	0.007	0.003	0.009
	Malnutrition or insufficient prenatal care	-0.003	0.010	0.005	0.011
	Diabetes	-0.010	0.006	-0.012	0.006
	Smoking, and alcohol or drug dependence	0.000	0.006	-0.002	0.006
	Infectious and parasitic conditions	0.006	0.004	0.006	0.004
	Heart diseases	-0.001	0.002	0.000	0.002
	Fetal abnormality	0.001	0.002	-0.001	0.003
	Antepartum fetal distress	0.000	0.001	0.000	0.001
	Hypertension	-0.009	0.006	-0.005	0.007
	Isoimmunization	-0.004	0.004	-0.002	0.004
	Premature rupture of the amniotic sac	0.000	0.003	0.005	0.004
	Other complications of pregnancy	0.001	0.003	0.003	0.003

Note: This table reports the estimates from individual regressions of patient characteristics on physician housing return (i.e., reversed cumulative housing return since purchase). The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. The sample period is 2007–2009. Corresponding coefficients are visualized in Figure 2.

Table A2. **Extended sample periods**

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section	Unscheduled C-section	C-section w/o ancillary procedures	Log(charges)	Length of stay (days)	Maternal infection
(A) Sample period: 2006						
All births (N=65,987)						
Physician housing return	-7.005	2.492	-6.671	-0.005	-0.093	-1.538
	[5.144]	[4.411]	[4.942]	[0.058]	[0.039]	[1.657]
Low-risk births (N=47,764)						
Physician housing return	-4.111	0.360	-4.834	0.025	-0.062	-3.294
	[6.693]	[5.127]	[6.257]	[0.063]	[0.049]	[2.020]
(B) Sample period: 2010–2012						
All births (N=155,027)						
Physician housing return	4.421	7.196	1.076	0.048	0.009	-0.766
	[3.121]	[1.961]	[2.854]	[0.079]	[0.024]	[0.560]
Low-risk births (N=108,474)						
Physician housing return	7.888	8.651	3.035	0.056	0.017	-0.617
	[3.895]	[2.577]	[3.229]	[0.086]	[0.029]	[0.778]
(C) Sample period: 2013–2015						
All births (N=130,875)						
Physician housing return	-0.044	-0.143	0.357	0.124	-0.051	-0.796
	[2.433]	[1.682]	[2.002]	[0.047]	[0.020]	[0.444]
Low-risk births (N=90,994)						
Physician housing return	-1.631	-0.045	-2.134	0.100	-0.068	-1.019
	[3.345]	[2.351]	[2.643]	[0.050]	[0.023]	[0.600]
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports linear regression results on the C-section rate with extended fixed effects. Dummy dependent variables are multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. Standard errors clustered at the physician level are in the brackets.

Table A3. Heterogeneous effect by patient characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				C-section			
Subsamples		Race and ethnicity			Income		Education
	Black	Hispanic	Non-black/Hispanic	Low	High	Low	High
(A) All births							
Physician wealth shock	6.690	1.052	1.833	2.263	3.012	3.187	2.185
	[1.622]	[1.389]	[1.050]	[1.135]	[1.061]	[1.117]	[1.083]
Mean of dep. var.	39.2	44.02	39.23	39.69	40.60	39.20	41.11
Obs	39,572	35,841	111,621	93,665	93,369	94,625	92,409
(B) Low-risk births							
Physician wealth shock	7.157	2.879	2.129	2.323	4.166	3.606	2.797
	[2.129]	[1.836]	[1.306]	[1.393]	[1.382]	[1.419]	[1.415]
Mean of dep. var.	22.38	25,15	22.04	22.76	22.62	22.05	23.34
Obs	27,391	24,727	80,891	66,475	66,534	67,148	65,861
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports sub-sample linear regression results on C-section rate by patient characteristics. The dependent variables are C-section dummies multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). Variable definitions for patient characteristics are described in Section 6.4.2. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

Table A4. Heterogeneous effect by patient characteristics (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section					
Subsamples	Predicted appropriateness for C-section			Insurance type		
	Low	Medium	High	Commercial	Medicaid	Others
(A) All births						
Physician wealth shock	2.639	3.624	1.900	2.188	3.297	1.745
	[1.362]	[1.402]	[1.008]	[1.095]	[1.179]	[2.133]
Mean of dep. var.	13.72	23.12	83.70	43.05	37.90	35.31
Obs	63,031	61,665	62,338	89,140	82,879	15,015
(B) Low-risk births						
Physician wealth shock	2.756	4.029	3.248	3.334	3.612	0.184
	[1.389]	[1.371]	[3.067]	[1.474]	[1.459]	[2.806]
Mean of dep. var.	13.88	22.89	55.12	24.85	21.12	18.76
Obs	59,702	57,442	15,865	62,943	59,308	10,758
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports sub-sample linear regression results on C-section rate by patient characteristics. The dependent variables are C-section dummies multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). Variable definitions for patient characteristics are described in Section 6.4.2. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

Table A5. Heterogeneous effect by physician characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				C-section			
Subsamples		Tenure			Gender		Loan-To-Value Ratio
	Junior	Medium	Senior	Male	Female	<100%	≥100%
(A) All births							
Physician wealth shock	4.884	-0.234	2.299	0.469	3.930	1.713	5.001
	[2.321]	[1.785]	[1.306]	[1.360]	[1.119]	[0.944]	[2.878]
Mean of dep. var.	39.53	40.57	40.21	41.23	39.27	39.76	41.41
Obs	62,140	61,226	58,188	83,319	103,715	143,994	43,040
(B) Low-risk births							
Physician wealth shock	5.328	-0.935	3.077	0.534	4.917	2.174	5.176
	[2.519]	[2.403]	[1.674]	[1.556]	[1.483]	[1.181]	[4.064]
Mean of dep. var.	22.70	22.27	23.07	23.47	22.08	22.45	23.51
Obs	44,698	43,006	41,454	58,878	74,131	102,704	30,305
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports sub-sample linear regression results on C-section rate by physician characteristics. The dependent variables are C-section dummies multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). Variable definitions for physician characteristics are described in Section 6.4.2. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

Table A6. **Heterogeneous effect by physician characteristics (continued)**

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section					
Subsamples	Physician ex-ante risk-adjusted C-section rate		Physician Competition			
			Market: zip code		Market: county	
	Low	High	Less competitive	More competitive	Less competitive	More competitive
(A) All births						
Physician wealth shock	0.969	4.081	3.242	1.758	3.362	2.362
	[1.020]	[1.240]	[1.780]	[1.923]	[1.219]	[1.914]
Mean of dep. var.	33.50	47.72	40.40	39.35	42.87	38.41
Obs	99,617	87,401	30,891	30,719	76,403	60,452
(B) Low-risk births						
Physician wealth shock	0.661	5.316	4.607	2.436	4.875	2.736
	[1.195]	[1.567]	[2.439]	[2.353]	[1.491]	[2.190]
Mean of dep. var.	17.56	29.03	23.15	22.07	25.53	20.71
Obs	73,524	59,478	21,598	21,969	53,337	43,401
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports sub-sample linear regression results on C-section rate by physician characteristics. The dependent variables are C-section dummies multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). Variable definitions for physician characteristics are described in Section 6.4.2. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

Table A7. Results using logit model

	(1)	(2)	(3)	(4)
Dep. var.	C-section	Unscheduled C-section	C-section w/o ancillary procedures	Maternal infection
(A) All births (N=187,034)				
Physician housing return	0.223	0.160	0.188	0.378
	[0.066]	[0.066]	[0.069]	[0.198]
Marginal effect	0.027	0.013	0.022	0.004
	[0.008]	[0.005]	[0.008]	[0.002]
(B) Low-risk births (N=133,009)				
Physician housing return	0.206	0.233	0.192	0.475
	[0.066]	[0.072]	[0.074]	[0.238]
Marginal effect	0.030	0.022	0.024	0.006
	[0.010]	[0.007]	[0.009]	[0.003]
Patient characteristics	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes

Note: This table reports results on the C-section rate using logit model. Dummy dependent variables are multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. The sample period is 2007–2009. Standard errors clustered at the physician level are in the brackets.

Table A8. Alternative clustering levels of standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section	Unscheduled C-section	C-section w/o ancillary procedures	Log(charges)	Length of stay (days)	Maternal infection
(A) All births (N=187,034)						
Physician housing return	2.717	1.297	2.200	0.055	0.014	0.379
s.e. clustered at ***hospital***	[0.704]	[0.556]	[0.786]	[0.022]	[0.006]	[0.175]
s.e. clustered at ***physician zip code***	[0.817]	[0.551]	[0.815]	[0.020]	[0.006]	[0.181]
s.e. clustered at ***patient zip code***	[0.712]	[0.543]	[0.682]	[0.009]	[0.006]	[0.176]
(B) Low-risk births (N=133,009)						
Physician housing return	3.298	2.450	2.664	0.061	0.011	0.578
s.e. clustered at ***hospital***	[0.852]	[0.709]	[0.965]	[0.023]	[0.006]	[0.235]
s.e. clustered at ***physician zip code***	[0.973]	[0.745]	[0.939]	[0.022]	[0.008]	[0.244]
s.e. clustered at ***patient zip code***	[0.916]	[0.709]	[0.858]	[0.011]	[0.007]	[0.216]
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports linear regression results on the C-section rate with standard errors clustered at alternative levels. Dummy dependent variables are multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. The sample period is 2007–2009. Standard errors are in the brackets.

Table A9. Alternative measures of housing return

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section	Unscheduled C-section	C-section w/o ancillary procedures	Log(charges)	Length of stay (days)	Maternal infection
(A) All births (N=187,034)						
(Reversed) Cumulative return since peak	11.235	4.553	8.910	0.250	0.055	1.529
	[3.996]	[2.613]	[4.075]	[0.107]	[0.031]	[0.749]
(Reversed) Cumulative return since 06Q4	11.119	4.396	8.926	0.249	0.054	1.538
	[3.980]	[2.610]	[4.069]	[0.107]	[0.031]	[0.751]
(Reversed) Cumulative return since purchase on time-varying portfolio	2.378	0.961	2.083	0.053	0.013	0.318
	[0.710]	[0.470]	[0.732]	[0.015]	[0.005]	[0.158]
(Lagged one quarter and reversed) Cumulative return since purchase	2.765	1.392	2.185	0.055	0.013	0.338
	[0.854]	[0.574]	[0.871]	[0.018]	[0.006]	[0.187]
(B) Low-risk births (N=133,009)						
(Reversed) Cumulative return since peak	11.235	4.553	8.910	0.250	0.055	1.529
	[3.996]	[2.613]	[4.075]	[0.107]	[0.031]	[0.749]
(Reversed) Cumulative return since 06Q4	11.476	6.254	8.060	0.274	0.074	2.303
	[4.916]	[3.466]	[4.711]	[0.110]	[0.034]	[0.973]
(Reversed) Cumulative return since purchase on time-varying portfolio	2.998	1.773	2.533	0.060	0.012	0.490
	[0.861]	[0.655]	[0.865]	[0.017]	[0.006]	[0.211]
(Lagged one quarter and reversed) Cumulative return since purchase	3.351	2.488	2.719	0.062	0.010	0.522
	[1.054]	[0.793]	[1.013]	[0.019]	[0.007]	[0.250]
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports linear regression results on the C-section rate using alternative measures of physician housing return. Section 6.5 describes the definitions of alternative measures. Dummy dependent variables are multiplied by 100 to ease interpretation. The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. The sample period is 2007–2009. Standard errors are in the brackets.

Table A10. Allowing physician turnover

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section	Unscheduled C-section	C-section w/o ancillary procedures	Log(charges)	Length of stay (days)	Maternal infection
(A) Allow late entries						
All births						
Physician housing return	2.912	1.403	2.409	0.064	0.015	0.427
	[0.853]	[0.559]	[0.869]	[0.019]	[0.006]	[0.188]
Low-risk births						
Physician housing return	3.500	2.585	2.824	0.069	0.013	0.624
	[1.040]	[0.778]	[1.015]	[0.020]	[0.007]	[0.254]
(B) Allow early exits						
All births						
Physician housing return	2.686	1.280	2.182	0.056	0.014	0.361
	[0.854]	[0.559]	[0.869]	[0.018]	[0.006]	[0.189]
Low-risk births						
Physician housing return	3.270	2.439	2.661	0.061	0.012	0.558
	[1.039]	[0.778]	[1.019]	[0.020]	[0.007]	[0.256]
(C) Allow both late entries and early exits						
All births						
Physician housing return	2.853	1.391	2.361	0.065	0.016	0.408
	[0.851]	[0.558]	[0.865]	[0.019]	[0.006]	[0.187]
Low-risk births						
Physician housing return	3.438	2.567	2.774	0.070	0.014	0.604
	[1.037]	[0.776]	[1.012]	[0.020]	[0.007]	[0.253]
Patient characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Physician FE	Yes	Yes	Yes	Yes	Yes	Yes
Hospital FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports linear regression results on the C-section rate using alternative samples that allow physician turnover. Dummy dependent variables are multiplied by 100 to ease interpretation. The independent variables are physician's housing returns (i.e., reversed cumulative housing return since purchase). The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. The sample period is 2007–2009. Standard errors are in the brackets.

Table A11. **The (semi-)wealth elasticities**

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	C-section	Unscheduled C-section	C-section w/o ancillary procedures	Log(charges)	Length of stay (days)	Maternal infection
(A) All births (N=187,034)						
Log(housing value)	-6.727	-3.092	-5.225	-0.151	-0.033	-0.909
	[2.575]	[1.665]	[2.607]	[0.069]	[0.020]	[0.470]
(B) Low-risk births (N=133,009)						
Log(housing value)	-6.923	-4.359	-4.770	-0.168	-0.046	-1.396
	[3.199]	[2.251]	[3.018]	[0.071]	[0.021]	[0.602]
Patient charateristics	Y	Y	Y	Y	Y	Y
Year-quarter FE	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y

Note: This table reports estimates for semi-elasticity of the C-section rate with respect to physicians' wealth. Dummy dependent variables are multiplied by 100 to ease interpretation. The independent variables are logged housing values. The regressions control for year-quarter, hospital, and physician fixed effects as in the baseline specification. The sample period is 2007–2009. Standard errors are in the brackets.

B Sample construction and descriptive statistics

B.1 Hospital inpatient discharges and physician characteristics

■ **Extraction.** I start 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 them, MS-DRG codes ″370″, ″371″, ″765″ and ″766″ indicate cesarean deliveries and codes ″372″, ″373″, ″374″, ″375″, ″767″, ″768″, ″774″ and ″775″ indicate vaginal deliveries. For these discharges, I can observe unique identifiers of both attending and operating physicians. There are two types of physician identifiers: (1) license IDs which are available for all years, and (2) NPIs which are only available since and after 2010. License IDs allow me to link physicians to the Florida″s health care practitioner profiles.[46] NPIs enable linkage to the National Provider Identifier (NPI) registry of National Plan and Provider Enumeration System (NPPES).[47] About 96–99% of the physicians can be found in the licensee profiles and NPI's physician files.

■ **Filters.** I perform the following filters based on the physician identifiers:

1. I drop physicians with license IDs of "nan", "999999999", or others shorter than 2 digits.
2. I keep physicians with license IDs that start with one of the following prefixes: ″MD″, ″ME″, ″OS″, ″TRN″, ″UO″ and ″ACN″. These are prefixes for "doctors", instead of nurses and midwives. ″TRN″ and ″UO″ are for resident physicians in training specifically.
3. I focus on physicians who have both non-missing license IDs and NPIs. This effectively restricts the sample to physicians who continue to show up in the data after 2010. This is to ensure that physicians can be linked to NPPES registry file.

■ **Defining maternal risk factors and morbidity.** I follow La Forgia (2022)'s program in coding maternal risk factors using ICD codes indicating risks present at the time of admission. See https://pubsonline.informs.org/doi/suppl/10.1287/mnsc.2022.4571 for details. I follow Johnson and Rehavi (2016), Freedman and Hammarlund (2019), La Forgia (2022), Callaghan et al. (2012), and Kilpatrick et al. (2016) in coding maternal morbidity using ICD codes indicating complications *not* present at the time of admission. The following table summarizes the 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

B.2 Physicians' houses

■ **Extraction.** I start with all ownership transfer records and mortgage records in CoreLogic. I keep records satisfying the following two conditions: (1) property location is in Florida, and (2) property type falls into one of the followings: single family residence, condominium, commercial, duplex, apartment. Restricting to

[46] See https://mqa-internet.doh.state.fl.us/downloadnet/Profile.aspx.
[47] See https://npiregistry.cms.hhs.gov/search. Data accessed on 2022/09/21.

properties physicially located in Florida is an expedient solution because it is difficult to search for a house owner just by name at the national scale. On the contrary, one can also focus on houses with "Buyer Mailing State" being Florida but that field is susceptible to more missing values in CoreLogic.

■ **Searching.** For each physician extracted from discharge records, I search within ownership transfer records and check if there are any associated transactions:

1. I first standardize the documented names from the physician files. For each physician, I construct a name combo: *Last Name + First Name + Middle Name Initial*. Most of the physicians have a name combo, except for a few with no names in either licensee profiles or from CMS.
2. For each transaction record, I standardize the buyer and seller names. If there are more than one name in either the field of buyer or the field of seller, I collect the names in a list.
3. I search for house transactions where either the buyer or the seller is a physician. I do this by *"role"* in a transaction (1: "BUYER 1", 2: "BUYER 2", 3: "BUYER 3", 4: "BUYER 4", 5: "SELLER 1", 6: "SELLER 2").

■ **Cleaning.** I start from the house transactions by physicians found in the previous step and build physicians' housing portfolios following the steps below:

1. I exclude house transactions that lack the following key information: property ID (CLIP), property location zip code, transaction date, sales amount.
2. I collapse the transaction-level data to doctor×house×date level. To do this, I first collapse the data into doctor×house×date×role level. For example, if a physician appears in different fields of "BUYER X", just take "BUYER". Then, for each house, keep the earliest purchase record and the latest sale record.
3. I calculate the number of transaction records within a pair of physician×house. I drop physicians whose number is greater than two. These are most likely the same buyer or seller appearing on different records of the same transaction. As a result, within a pair of physician×house, there are four types of transactions for a given pair of physician×house:
   - "Sell-first-then-buy": I drop these pairs.
   - "Buy-first-then-sell": I keep these pairs.
   - "Buy-only": I keep these pairs,
   - "Sell-only": For those records, I assign a pseudo purchase year based on median purchase year within the same 5-digit zip code. For a minority of transactions in zip codes that do not have such an empirical distribution, assign the median purchase year at the state level (i.e., 2005). These pairs then become "buy-first-then-sell" and so I can keep them.
4. I drop physicians who have transacted more than 10 different houses over the years. These are most likely poor matches due to common names.
5. I merge in mortgage information. This step doesn't lose any observation. Houses that have no matched mortgages are assumed to be purchased in cash.

The following table summarizes the attrition rates of each step above:

Step	# of houses	% of houses in the raw sample	# of physicians	% of physicians in the raw sample
0	102,975	100%	14,376	100%
1	89,145	86.57%	13,871	96.49%
2	88,503	85.95%	13,847	96.32%
3	88,455	85.90%	13,846	96.31%
4	32,457	31.52%	12,578	87.49%

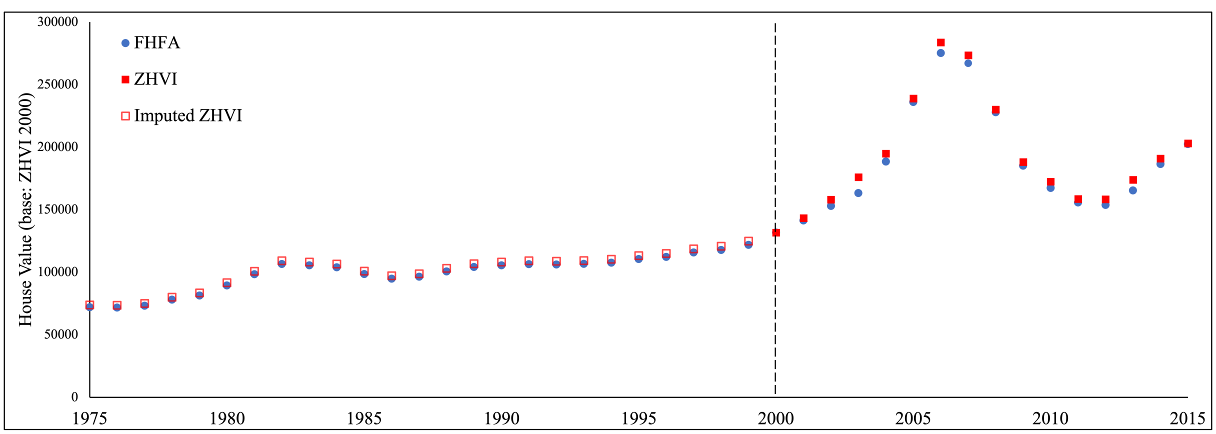
■ **Quality of matching.** I can take a snapshot for a given point of time and evaluate the quality of matching by checking how close the matched houses are to physicians' hospitals, and how close the matched houses are to physicians' patients. In measuring the distance from physicians' houses to their main hospitals, an area is a region defined by Florida AHCA which consist of a handful of adjacent counties. There are 11 regions in total.

In measuring the distance from physicians' houses to their patients, an area is a 3-digit zip code. There are 26 such 3-digit zip codes in the data. These percentages are based all the attending and operating physicians in the raw inpatient sample, not necessarily those included in the final analytical sample. The excluded physicians from these steps do not enter the regression analysis because they are neither well-defined "homeowners" nor "renters", but just washed out by the imperfect matching. The following table reports the quality of matching.

	How close are the matched houses to physicians' ***hospitals***	
Housing portfolios	% of houses in the same area where the physician does most of her procedures	% of physicians who have at least one house in the same area where he does most of her procedures
Pooling all together	49.72%	70.49%
Fixed at 2005-12-31	50.41%	73.64%
Fixed at 2006-12-31	50.42%	73.48%
Fixed at 2007-12-31	51.47%	73.68%
Fixed at 2008-12-31	51.74%	73.5%
	How close are the matched houses to physicians' ***patients***	
Housing portfolios	% of houses in the same area where most patients of the physician come from	% of physicians who have at least one house in the same area where most of her most patients come from
Pooling all together	45.6%	65.89%
Fixed at 2005-12-31	47.28%	70.69%
Fixed at 2006-12-31	47.23%	70.48%
Fixed at 2007-12-31	48.07%	70.49%
Fixed at 2008-12-31	48.35%	70.31%

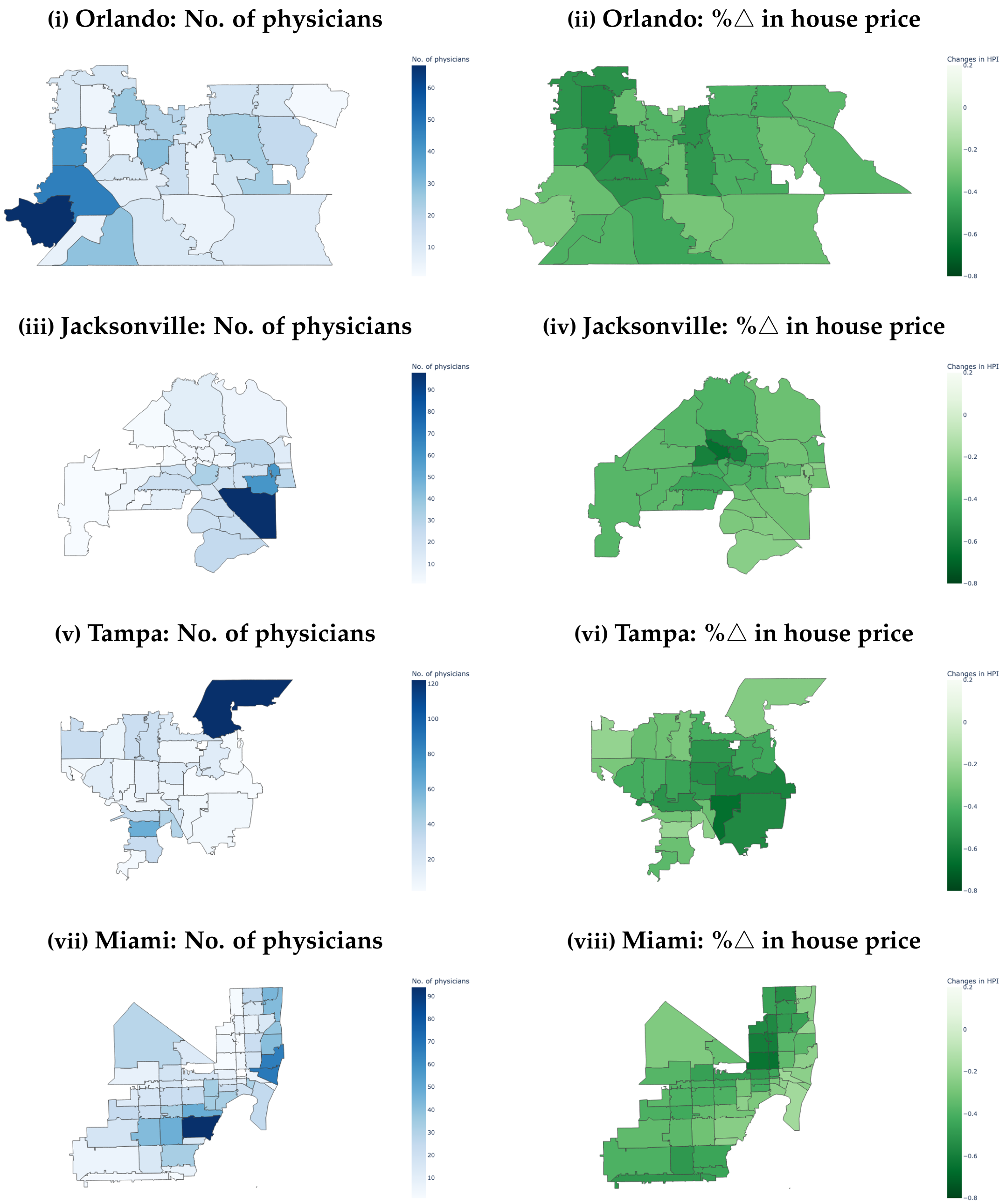
B.3 House price index

The Zillow House Value Index (ZHVI) is only available from year 2000. However, there are some physicians who purchased their houses before 2000. To avoid dropping these physicians, I impute ZHVI's missing values using FHFA's house price index. Although only published annually, FHFA's index dates back to as early as the 1970s and is also available at the zip code level Bogin et al. (2019). For each zip code that exists in both ZHVI and FHFA after 2000, I calculate an average conversion ratio between ZHVI and FHFA: $\gamma = \frac{1}{T}\sum_{2000\leq t\leq T}^{T} \frac{HPI_t^{\text{ZHVI}}}{HPI_t^{\text{FHFA}}}$. The ratio captures how close these two indices are, although they cannot be compared directly because of different units. The ZHVI values for a given zip code before 2000 are then given by by: $HPI_t^{\text{ZHVI}} = \gamma \cdot HPI_t^{\text{FHFA}}, \forall t < 2000$. The Following figure shows that the *average* imputed ZHVI values.



B.4 Additional descriptive statistics

Figure B2. Geographical variation in Physician housing return



Notes: On the left column are number of physicians residing in each zip code calculated using data in the labor and delivery sample. On the right column are percentage changes in house price by 5-digit zip code calculated using raw ZHVI data. Zip codes without data are not filled with colors.

Figure B3 shows the number of physician buyers in the matched data by year (up to 2006).

Figure B3. Percentage of physicians purchasing houses in different years

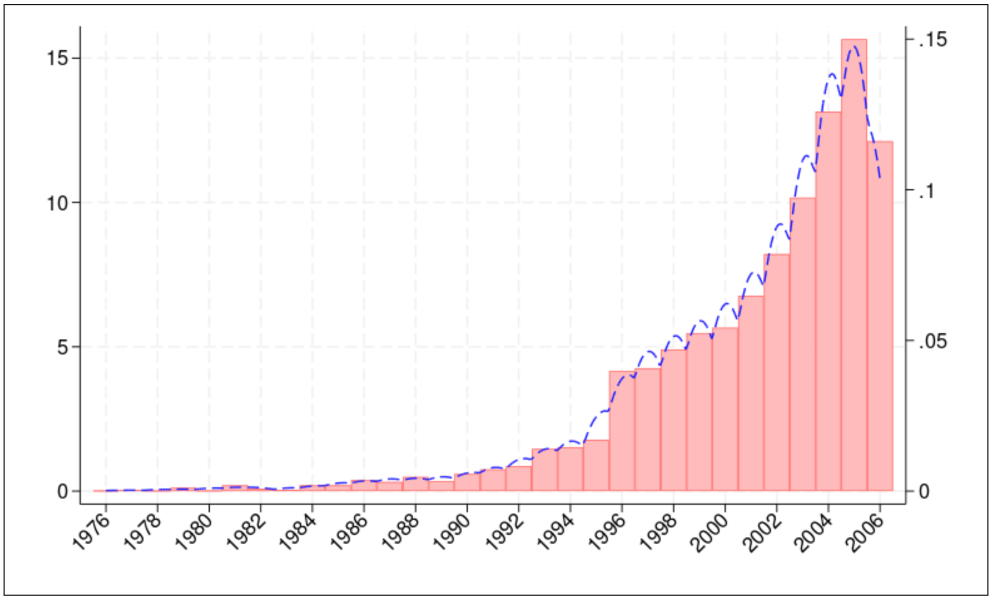


Figure B4 depicts the simulated changes in house price from 2007 to 2012 had a physician purchases her house at different time. If he purchased the house in 2000 when price level was relatively low (i.e., the blue bars), he would have enjoyed over 100% of premiums in an average zip code by 2007. Even though in year 2012 when the market recorded the lowest level, he would still maintain a positive return on average. On the other hand, if he purchased the house just before the crisis in 2006 (i.e., the green bars), he would quickly go into negative returns as the housing bust develops. This group of physicians can lose up to nearly 50% of her house equity by 2012 in an average zip code.

Figure B4. Timing of transaction and housing return