Does Your Reputation Precede You? The Role of Malpractice History in the Demand for Specialist Physicians

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Abstract

Do patients or their doctors care about a specialist's malpractice history? I answer this question by estimating a discrete choice model of demand for knee and hip replacement surgeons in Florida. I find that physicians experience a statistically significant, but economically modest, loss of demand from having a history of being sued. A sued physician is 0.256 percentage points less likely to be chosen to perform a knee or hip replacement surgery. However, the biggest drop in demand occurs after one suit, the effect persists over time, and patients do not care whether the specialist successfully defends her lawsuits.

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1 Introduction

In the United States, medical practice is regulated by state boards of medicine. Patient advocates frequently criticize medical boards for being overly solicitous of doctors. One alternative to regulatory supervision is the private tort action of medical malpractice. But medical malpractice is not without its drawbacks. Specifically, physicians, regulators, and scholars are concerned about "defensive medicine," whereby physicians treat patients differently——either by ordering unnecessary tests, diagnostic procedures, or referrals, or by avoiding risky, but necessary procedures——solely to avoid being sued for malpractice.

While the true scope of defensive medicine remains an open question, research shows that physicians are quite sensitive to the prospect of being sued. It is not clear what motivates such sensitivity because evidence suggests that doctors are rarely sued even when they have been negligent (Localio et al. 1991). Moreover, when they are sued, doctors do not lose significant amounts of money or time. This disconnect between the reality of malpractice exposure and physicians' responses thereto motivates this paper. Specifically, I examine one possible explanation proposed by the literature more plausible than direct pecuniary loss: reputational harm.

A physician could plausibly suffer reputational harm from the disclosure of a malpractice suit in several different ways. First, it could be bad for business. Patients may learn about a physician being sued for malpractice and decide to go to another doctor or other doctors may learn about the lawsuit and shift their referrals away from the sued doctor. Second, it could threaten doctors' admitting privileges or other professional relationships. Hospitals, for example, are required to query the National Practitioner Data Bank (NPDB), which reports all payments made to resolve a medical malpractice claim, when considering professionals' applications for clinical privileges. Anecdotally, doctors report some degree of anxiety about being reported in the NPDB, and Waters et al. (2003) claim that this fear of being reported to the NPDB changed medical malpractice litigation dynamics in the 1990s.

Third, doctors likely value their reputation as a good in and of itself, and a malpractice action against them could damage this good.

This paper focuses on the first of these mechanisms. I ask, do malpractice lawsuits reduce the demand for physician services? The literature has speculated about the possibility of reputational harm to physicians from being sued for malpractice (Mello et al. 2010). Some authors have even suggested that concerns over reputational harm are the primary motivation for defensive medicine (Currie and MacLeod 2008). However, to the best of my knowledge, I am the first to test for this phenomenon empirically.

To answer my research question, I turn to data on medical malpractice lawsuits and elective hospital discharges from Florida. Florida is unique among U.S. jurisdictions in the transparency of its medical malpractice lawsuit data. The Florida Office of Insurance Regulation (FLOIR) maintains a rich dataset of malpractice claims, which it makes available online for free. Not only does this facilitate academic research on the subject, but it also means that patients and referring physicians have access to information about a physician's malpractice history.

I combine this lawsuit data with the universe of elective inpatient discharges from Florida for the years 2010—2014. Other researchers have combined these datasets in the past. However, while Carroll, Cutler, and Jena (2021) look at emergency room discharges and Black, Wagner, and Zabinski (2017) connect variables derived from the discharge data to lawsuits against hospitals, I link the lawsuit data to attending physicians for elective inpatient discharges.

In particular, I consider elective discharges for the DRG pair 469–470, knee and hip replacement surgery. These procedures are almost always elective and take place in an inpatient setting. Thus, these discharges most likely reflect the decision making process I model, a deliberate choice for a specialist physician, at least possibly made in consultation with a primary care provider. Estimating the reputational impact of a specialist's malpractice history requires that a patient–referring physician pair have the time and space to search for a specialist and consider his or her reputation.

I first use the discharge data to identify which knee and hip replacement surgeon a patient chose. I also use this data to see which knee and hip replacement surgeons saw patients in which geographic markets and in which quarters. This allows me to construct choice sets by identifying the physicians a patient could have seen but chose not to.

With these choice sets in hand, I estimate a discrete choice model of demand for knee and hip replacement surgeons. My primary explanatory variables of interest come from the Florida medical malpractice lawsuit data. I supplement these variables with data on physician characteristics from the Medicare Data on Provider Practice and Specialty (MD-PPAS) and Physician Compare (PC) data sets. Variation comes from differences between physicians, over time, and between markets.

I find that the demand for physician services is indeed less for those with more extensive malpractice histories, but this effect is small. Specifically, a physician who is sued for malpractice is 0.26 percentage points less likely to be chosen to perform a knee or hip replacement surgery. This represents a roughly 10.35 percent decrease relative to the average probability of selection. However, the biggest loss in demand occurs after a doctor's first lawsuit. These effects appear to be persistent over time, and patients and referring physicians do not seem to care how much a physician pays out in damages.

My primary specifications assume that a patient or referring physician learns about a specialist's malpractice history by querying FLOIR's free online search portal. However, it is possible that a decision maker learns about a specialist's malpractice history by looking on the Florida Department of Health (DOH) practitioner profile or that a referring physician—but not a patient—learns of a specialist's malpractice history by querying the NPDB. Each of these alternative disclosure mechanisms involves different criteria for which suits are reported. When I assume that a decision maker learns about a specialist's malpractice history through one of these alternative mechanisms and re-estimate the demand model accordingly, my main results do not change substantially.

My findings likely represent the upper bound on the effect size of being sued. Florida is remarkable in its degree of transparency over medical malpractice; in other jurisdictions, it is far less likely that a patient or a referring physician will be able to learn of a physician's being sued for malpractice. Thus, reputational loss in the form of decreased demand is likely even less significant in states other than Florida.

This paper proceeds as follows. In Section 2, I provide some background on how malpractice lawsuits (and the perceived risk thereof) have been show to affect physician behavior. In Section 3, I describe the data I use to undertake this study. I describe how I use this data to construct an analytic sample and discuss some summary statistics in Section 4. Next, I discuss the discrete choice methods I use in Section 5. In Section 6, I discuss my results and in Section 7, I briefly conclude.

2 Background on Medical Malpractice

Ample evidence demonstrates that malpractice liability (and the perceived risk thereof) affects physician behavior. Studies have shown that legal malpractice standards influence physician procedure use (Avraham and Schanzenbach 2015; Frakes, Frank, and Seabury 2015; Frakes 2013; Currie and MacLeod 2008; Fenn, Gray, and Rickman 2007) and specialty choice (Frakes, Frank, and Seabury 2020). Carroll, Cutler, and Jena (2021) show that physicians who are sued—as opposed to merely being afraid of a possible future lawsuit—treat fewer patients and treat those patients more expensively in the aftermath of a lawsuit, regardless of that lawsuit's outcome. In a survey, 92 percent of responding physicians claim to order unnecessary tests, perform unnecessary diagnostic procedures, or refer patients unnecessarily to avoid being sued for malpractice (Studdert et al. 2005).

The motivating factors behind physician sensitivity remain unclear. Defensive medicine practices are correlated with physicians' subjective concern about malpractice liability risk, but these practices are not correlated with objective measures of actual liability risk (Carrier et al. 2013). Moreover, physicians do not suffer substantial time or money losses as a result of being sued for malpractice. Doctors only lose 2.7–5 days per claim to malpractice lawsuits (Mello et al. 2010). In addition, doctors almost never have to pay any amount of malpractice damages out of pocket. Looking at closed malpractice claims in Texas from 1990 to 2003, Zeiler et al. (2007) observe that physicians personally contribute to awards or settlements in less than 1 percent of all cases. While that number is slightly higher in the data set I consider in this paper at 1.81 percent, I observe a pattern in Florida that is similar to what is observed in Texas. As shown in Figure 1, there is a sharp discontinuity in payments at the per-claim maximum—the threshold where physicians would have to start paying for malpractice damages out of pocket. Figure 1 further shows that the modal payment to plaintiffs in medical malpractice cases in Florida is $0.

Furthermore, medical malpractice insurance involves relatively little cost sharing. Of the physicians performing knee and hip replacements in Florida between 2010 and 2014 who have been sued, 97.4 percent had a zero-dollar deductible. Because I only observe deductibles conditional on having been sued, I hesitate to draw any strong conclusions from this statistic. Nevertheless, this number is high enough to suggest that zero-dollar deductibles are widely available.

While malpractice insurance premiums can be high, they do not necessarily change much after being sued. Under community rating, all insurance holders pay the same premium, regardless of their history or individual characteristics. Under experience rating, a policy holder's premium is determined by the policy holder's individual characteristics and claims history. Medical malpractice premiums are primarily determined by specialty and geographic practice area. Although Florida law requires some amount of experience rating,[1] experience

[1] Fla. Stat. Ann § 627.062(7)(d).

rating is limited in practice. Sometimes insurers meet this obligation by offering discounts to entire hospital practice groups that have implemented safety protocols. A more typical form of experience rating comes in the form of increasingly large discounts for a greater number of claim-free years, but a claim usually does not count towards this scheme unless payments associated with the claim exceed tens of thousands of dollars. For example, under policies offered by the Doctors Company, a popular malpractice insurance carrier in Florida, total indemnity payments of less than $50,000, which account for 54 percent of all claims in my sample, do not affect a policy holder's claim-free discount.

Physician concern about reputational harms may explain the relationship between malpractice lawsuits (or fear thereof) and physician behavior. Unless specifically made confidential, filings in lawsuits are matters of public record. Even if the average member of the public does not regularly comb through court documents, journalists often do, and they may direct media attention to a lawsuit. In addition, federal law requires any entity making a malpractice payment to disclose that payment to the National Practitioner Data Bank (NPDB). Though the NPDB is generally confidential,[2] hospitals, professional societies, and other entities with peer review can query the NPDB and thereby learn about the lawsuit and its underlying circumstances. In my data setting of Florida, comprehensive data on medical malpractice claims is publicly available through the Florida Office of Insurance Regulation's website, and limited information on malpractice history is part of the Department of Health's practitioner profiles. Even absent these disclosure mechanisms, news of a lawsuit would likely spread by word-of-mouth through a physician's personal and professional circles.

In this paper, I ask how much of a role a physician's malpractice history plays in the demand for his or her services. This paper primarily contributes to two strands of literature: healthcare services demand estimation and inquiries into the effects of medical malpractice lawsuits on physician behavior.

[2] Indeed, while the NPDB publishes an anonymized public data file, researchers accessing this data must specifically agree that they will not attempt to use any of the data to identify a provider listed in the report.

Many studies have estimated patient demand for hospital services, either for its own sake or as part of a structural model to estimate the effects of, for example, hospital mergers or price negotiations between hospitals and insurers (Ho and Lee 2017; Gowrisankaran, Nevo, and Town 2015; Beckert, Christensen, and Collyer 2012; Gaynor and Vogt 2003; Kessler and McClellan 2000; Romley and Goldman 2011; Tay 2003). These papers generally find "cost, distance to patient's residence, and measured quality" to be of particular importance to patient hospital choice (Baker, Bundorf, and Kessler 2016). However, none of these studies have looked specifically at the demand effects of malpractice lawsuits.

It is important here to distinguish malpractice lawsuits and other legal sanctions from measures of healthcare quality. Previous studies have used, for example, mortality rates, waiting times, and MRSA infection rates as quality metrics (Beckert, Christensen, and Collyer 2012). There are sound reasons for doing so. But because this study is particularly interested in why physicians are so responsive to the risk of malpractice lawsuits, this paper is more concerned with actual exposure to such lawsuits, separate and distinct from any quality metrics.

The impact of medical malpractice lawsuits on physician behavior has been of perennial interest to economists. As discussed above, ample research has explored the relationship between physician behavior and malpractice law (Frakes, Frank, and Seabury 2020, 2015; Avraham and Schanzenbach 2015; Frakes 2013; Currie and MacLeod 2008; Fenn, Gray, and Rickman 2007) or actual malpractice lawsuits (Carroll, Cutler, and Jena 2021).

In addition, many papers have considered malpractice laws and system level outcomes. Roberts and Hoch (2009, 2007) find that malpractice lawsuit incidence is positively associated with healthcare expenditures. Kessler and McClellan (1996) categorize various elements of state tort reform packages into "direct" and "indirect" measures and evaluate their impact on expenditures and health outcomes for Medicare beneficiaries with acute myocardial infarction or ischemic heart disease. Kessler and McClellan (1996) define "direct measures" to be caps on damage awards, abolition of punitive damages, the elimination of mandatory prejudgment interest, and collateral-source rule reform, and "indirect measures" to be caps on contingency fees, mandatory periodic payments, joint-and-several liability reform, and changes to patient compensation funds. Using difference-in-differences, they find that direct measures reduce expenditures while having no significant impact on health outcomes. In their follow-up paper, Kessler and McClellan (2002) explore the mechanism of tort reform. They find that it operates by reducing claim rates and compensation conditional on claim filing and that defensive medicine has a larger impact on diagnostic procedures than treatment procedures.

Several papers concur with the findings of Kessler and McClellan. Avraham, Dafny, and Schanzenbach (2010) and Avraham and Schanzenbach (2015) conclude that tort reform measures lower employer-sponsored health insurance premiums by about 2.1% and affect the treatment behavior of physicians. Similarly, Fenn, Gray, and Rickman (2007) identify a positive association between malpractice liability exposure and the rate of diagnostic procedures using an administrative quirk of England's National Health Service as an instrument for expected malpractice liability costs. More recently, Frakes and Gruber (2019) take advantage of the *Feres* Doctrine and military base closures to show that immunity from malpractice liability reduces inpatient spending 5 percent with no effect on health outcomes.[3]

On the other hand, several studies have found no evidence of defensive medicine. Paik, Black, and Hyman (2017) find that the introduction of damage caps had no impact on Medicare Part A spending and, counter to the arguments of tort reformers, increased Medicare Part B spending by 4 percent. In addition, Sloan and Shadle (2009) find that the direct and indirect tort reforms identified by Kessler and McClellan (1996) have little or no impact on physician behavior, patient outcomes, and Medicare expenditure. However, these

[3]Under *Feres v. United States*, 340 US 135 (1950), service members—–but not their families—–are barred from suing the United States for injuries resulting from the negligence of others in the armed forces.

studies do not focus on the specific incentives faced by physicians, nor do they acknowledge physicians' limited financial exposure to malpractice liability. Currie and MacLeod (2008) and Carroll, Cutler, and Jena (2021) are notable exceptions here, but even these papers do not empirically test an alternative source of physician malpractice disutility. Currie and MacLeod (2008), for example, posit the role of reputational harm to physicians estimate a model where the probability of suit matters more to physicians than total damages. But, they do not actually test whether their posited reputational harms exist.

This paper seeks to fill that gap and explain why, in the absence of direct financial costs, physicians are sufficiently sensitive to the prospect of malpractice lawsuits as to alter their treatment behavior. This paper specifically considers reputational harm as a possible source of physician disutility. To my knowledge, there are no published estimates of the reputational harm from being sued for medical malpractice. Estimating these effects provides valuable insight into physician behavior that can help inform policy debates about the healthcare industry generally and malpractice related tort reform in particular.

3 Data

This paper primarily relies on Florida administrative data for two main reasons. First, because Florida is a long peninsula, geographic markets are less likely to cross state borders than would be the case elsewhere. Second, Florida maintains—and makes available to researchers—an impressive quantity of data on medical malpractice lawsuits and inpatient hospital stays.

3.1 Florida Professional Liability Claims Reports

For variation in physician malpractice history, I primarily rely on the Florida Professional Liability Claims Reporting Database (PLCR) (Florida Office of Insurance Regulation 2025). Florida law requires entities insuring physicians and hospitals against medical malpractice liability to report all closed claims to the FLOIR.[4] Unlike most states' insurance regulators, the FLOIR makes this and other data publicly available through the PLCR, which represents a near universe of medical malpractice claims. Technically, if the defendant-physician prevails with less than $5,000 in loss adjustments for the insurer, then the claim need not be reported to the FLOIR. However, this is relatively uncommon, and insurers appear to report even these claims in practice. The PLCR database contains information on the name and professional license number of the defendant provider; dates for the injury, the filing of the complaint, and the disposition of the action; and information on the indemnity payment and loss adjustment of the insurer. Observations in the PLCR online database are organized by claim. I use the PLCR to determine how many times a physician has been sued, when they have been sued, and how much was paid to the plaintiff-patient as a settlement or award.

3.2 Florida Hospital Inpatient File

The Florida Agency for Health Care Administration publishes the Hospital Inpatient File (HIF), which contains data on inpatient discharges (Florida Agency for Healthcare Administration 1999–2014). This data set includes the entire universe of inpatient discharges, is unique to the discharge level, and identifies the time of discharge by year and quarter. This data set includes information about the hospital and identifies the attending and operating physicians by medical license number and national provider identification (NPI) number. It also lists information about patient characteristics (including sex, race, age, and zip code). In addition, this data set contains variables for the priority of the admission (e.g., elective vs. urgent vs. emergency), the principal procedure code, a diagnostic-related group (DRG) code, and the admitting and principal diagnoses.

I use the Florida discharge data for several purposes. First, I use it to identify patient safety indicator (PSI) events, which I then aggregate to PSI rates. Second, I use it to construct geographic markets for specialist physicians. Third, I use the HIF data to

[4] Florida Statutes § 627.912 (2021)

construct each patient's choice set and identify the doctor chosen. I discuss these steps in greater detail below.

3.3 Other Data

Since the Florida discharge data contain both the physician's license number and NPI, I am able to include additional information about each doctor found in other, publicly available data sets. The Medicare Data on Provider Practice and Specialty (MD-PPAS) data set provides each physician's specialty and the zip code of her primary practice location (Centers for Medicare and Medicaid Services 2009–2014). I use the latter to calculate distance between patients and physicians' primary practice locations—or, rather, between their zip code centroids.

Physician Compare (PC) further provides data on each physician's gender and medical school graduation year (Centers for Medicare and Medicaid Services 2014). Medical school graduation year allows me to calculate physician tenure. The first year PC is available, 2014, is at the end of my sample period. However, the variables provided by PC are time-invariant, so this would only be a concern if either a very large portion of the sample retired before 2014 or if malpractice lawsuits drove sued physicians to retire earlier than their unsued counterparts. That latter scenario could bias my estimates toward zero because I would not be accounting for reductions in demand so extreme that they drive physicians out of practice. In actuality, only about 4.7 percent of the sample fails to merge with the 2014 PC data—due to retirements or other reasons—and these physicians have similar malpractice histories to those who remain. Furthermore, estimates that include these physicians are similar to those that exclude them, though of course I cannot compare the estimates with fully specified models.

4 Sample Construction and Summary Statistics

4.1 Patient Safety Indicators

I construct a doctor-specific patient safety measure to control for overall physician safety. To construct this variable, I apply the definitions for Patient Safety Indicators (PSI) developed by the Agency for Healthcare Research and Quality (AHRQ) to the HIF. The PSIs were designed to identify preventable adverse events—that is, provider error. Each PSI describes a particular type of error. For example, PSI 3 is for pressure ulcers.

The PSIs are designed to be aggregated to the provider level, though most of the PSIs can be applied to an individual discharge (some are rates that only apply to entire metropolitan areas). I use most (PSIs 3–16) of the PSIs that can be applied to an individual discharge, and I omit PSIs 17–19, which are for obstetric discharges only. I attribute errors to the attending physician.

AHRQ developed these indicators to identify more preventable adverse events and to avoid false positives. To do this, AHRQ excludes patients who would likely have suffered an adverse outcome without provider error from consideration. The PSIs avoid false positives at the cost of missing true positives. As a result, according to Classen et al. (2011), the PSIs have a specificity of 98.5 percent, and a sensitivity of 5.8 percent. For a more thorough discussion of PSIs, see Black, Wagner, and Zabinski (2017).

To see how this classification scheme works, consider PSI 13, postoperative sepsis. A patient would be considered at risk of PSI 13 if and only if she had an elective surgery discharge and any listed operating procedure and did not meet an exclusion criterion. The patient would be excluded if she had a diagnosis for sepsis, pressure ulcer, cancer, immunocompromised state that was present on admission. A patient would also be excluded if her stay lasted less than four days, or if her record had missing data for sex, age, quarter, year, or principal diagnosis. If deemed at risk, a patient would then be flagged for PSI 13 if her record also contained one of 21 ICD-9 codes related to a sepsis diagnosis. If the patient is at risk of PSI 13 but her record lacks all of those 21 diagnosis codes, then she would not be flagged for the PSI. If the patient was not at risk of PSI 13, then the PSI definitions would neither classify her as at risk for PSI 13 nor flag her record for PSI 13, even if she otherwise had one of the 21 sepsis-related diagnosis codes in her record.

After identifying all the inpatient discharges that are at risk of or flagged for a PSI, I aggregate these to the physician level. To capture underlying safety characteristics of physicians and avoid double-counting, I omit any discharges at risk of or flagged for a PSI in any quarter in which a doctor's alleged acts or omissions led to a malpractice lawsuit. For each physician and each quarter, I then sum all PSI flagged events and divide by the sum of all at-risk events in the preceding twelve, sixteen, twenty, twenty-four, and twenty-eight quarters. I then multiply by $1,000$ to obtain the rate of PSI events per $1,000$ at-risk discharges.

While PSI events appear to be correlated with medical malpractice lawsuits against hospitals (Black, Wagner, and Zabinski 2017), there is no such correlation in my sample. After excluding PSI events that occur in the same quarter as an act or omission leading to a lawsuit, the correlation coefficient for rate of PSI events in the previous four years and the number of lawsuits in the previous four years is -0.005. Estimating the models without the PSI rates does not change any result.

To assess whether an adverse outcome occurred as the result of medical error, many of the PSIs rely on "present on admission" (POA) codes to determine if, for example, a patient arrived at the hospital with an infection or if that infection was acquired at the hospital. The HIF only begins including these POA codes comprehensively in 2007, so my lookback period length determines the starting point of my sample period and vice-versa.

4.2 Sample Construction

I construct my analytic sample by first looking at all inpatient discharges for DRGs 469 and 470—major joint replacement or reattachment of lower extremity with and without major complications or comorbidities. While this DRG pair technically includes ankle replacements, that is a very rare procedure, so DRG pair 469-470 can be thought of as knee and hip replacements (Karzon et al. 2022). These procedures are ideal for this study because they are overwhelmingly elective in nature. In addition, during the sample period, knee and hip replacement surgeries were most likely to occur in an inpatient setting for the Medicare population. This latter criterion is particularly important because it means that if a patient sought a knee or hip replacement during the sample period, I would observe it in the HIF data. I drop all nonelective procedures.

I limit my sample to patients whose primary payer is Medicare Fee for Service (FFS). The HIF payer data only indicates whether the primary payer was Medicare FFS, Medicare Advantage (MA), Medicaid, a private insurance company, or some other entity; it does not say which insurer covered an MA, Medicare managed care, or privately insured patient. As a result, I cannot infer an patient's network of providers from the HIF data. I avoid the problem of unobserved choice sets by assuming that any provider in a market is willing to see Medicare FFS patients. To simplify the analysis, I only consider patients with Florida zip codes and physicians whose primary practice location is in Florida.

I further limit my sample to the years 2011–2014. I only look at patient visits after 2010 because that is the first year that the HIF records attending physicians' NPIs, and that variable is important to merge in the MD-PPAS and Physician Compare data sets. In addition, as I explore below, I ultimately use a four-year lookback period for time-limited variables. Because the POA codes are only available starting in 2007, as explained above, this makes 2011 the first year of the sample.

My sample period ends in 2014 because the PSI definitions depend on ICD codes.

In the last quarter of 2015, the HIF changes from reporting ICD-9 to reporting ICD-10 codes. To avoid straddling this divide and to maintain time-consistency, I consider discharges prior to 2015 for ease of exposition. Looking at discharges from 2015Q4 onwards can be problematic because medical malpractice cases typically take around four years to resolve in Florida (which is consistent with cases malpractice cases nationally) (Markowitz and Smith 2023). This means that any case arising out of an occurrence in 2016 onward might still have been unresolved as of the onset of the COVID-19 pandemic, which disrupted court functioning in ways that likely distorted litigation incentives. Even if this were not the case, many hospitals cancelled or delayed elective procedures during much of 2020–21. Therefore, only observations through 2019 should be included in the post-2015 period. This would leave fewer years of observations than the 2011–2014 period that I ultimately opt for.

Table 1 reports the summary statistics for knee and hip replacement surgeons. Because the variables relating to malpractice history are time-varying and accumulate over time, these sample statistics are taken across all orthopedic surgeons for the latest quarter each is present in the sample. Approximately 38.9 percent of all surgeons who perform knee and hip replacements in Florida have been sued for malpractice, and the average number of lawsuits is approximately 0.8 per physician overall. Conditional on being sued, the average number of suits is 2. Figure 2 shows the distribution of the number of total lawsuits in a physician's past. It is relatively common to have been sued up to 3 times, and anything more than that is rare. This distribution is similar to that of emergency medicine physicians (Carroll, Cutler, and Jena 2021).

Table 2 shows how doctors who have and have not been sued compare. Doctors who have been sued actually have fewer PSI events per 1000 at-risk patients than doctors who have not been sued, though this difference is neither large nor statistically significant. Doctors who have been sued see more patients and have been practicing longer on average. These differences are significant and likely related. To the extent that being sued for malpractice has a mechanical relationship to the number of patients a physician has seen, it would make sense that doctors who are sued have seen more patients over a longer career. Doctors who are sued are significantly less likely to be female.

It appears that surgeons see fewer patients in the quarters following a lawsuit being reported to the PLCR. Figure 3 shows the average patient volume for physicians that have been sued, relative to physicians that have not been sued, in the quarters before and after their suits are reported to the PLCR. In the twelve quarters prior to the suit being reported, physicians who are sued treat 77.43 more patients than doctors who are not sued. In the twelve quarters after having their suit reported, sued physicians see only 20.68 more patients than unsued physicians.

4.3 Choice Set Construction

I use the Dartmouth Atlas Hospital Referral Regions (HRRs) as the local geographical markets for specialist physicians for my primary specifications. HRRs are appropriate for this study because they agglomerate zip codes based on elective hospital visits (Wennberg and Cooper 2022). The Pensacola, Dothan, Tallahassee, and Jacksonville HRRs all straddle Florida's borders with Alabama and Georgia. To avoid the problem of unobserved choice sets, I drop all visits from patients living in these HRRs.

While the Dartmouth Atlas HRRs are commonly used (Sarsons 2017; Zeltzer 2020) to define local physician markets, they are not without their critics. The HRRs were derived from Medicare inpatient data from the years 1992–1993, and technological, business, and market changes since then may have led to changes in patient–hospital flows. Jia, Wang, and Xierali (2020) show that *contemporary* HRRs—those drawn using the Dartmouth Atlas's methodology and criteria but based on discharges from 2011—in Florida are more numerous and compact while not any less self-contained than the Dartmouth Atlas HRRs. In addition, the Darthmouth Atlas HRRs were formed using cardiovascular surgery and neurosurgery discharges (Wennberg and Cooper 2022). Patients may be willing to travel different distances for these procedures compared to hip and knee replacement surgeries, which could limit the usefulness of HRRs for this study.

Since the Florida discharge data identify discharges by quarter, each market for my demand estimation is a market-quarter. I then impute choice sets to each discharge. I assume that a patient could have seen any physician practicing in a geographic market in that quarter. I define a physician as practicing "in" a geographic market if, in that quarter, the physician sees more than five patients and more than five percent of all her patients in that market in that quarter. While this definition appears incredibly inclusive, it actually excludes about 9 percent of all visits. As shown in the Appendix, my results are generally robust to alternative specifications for practicing 'in' a market. The sign never flips, and the magnitudes are, for the most part, within a relatively close range. When the threshold number of patients for practicing in a market is increased to 30, I do see results that are larger in magnitude. However, limiting patients' choice sets in this way excludes 43 percent of inpatient stays, which is likely overly restrictive. Under any of these definitions, physicians can practice in more than one market at any given time.

To avoid the issue of unobserved insurer–provider networks, I only consider patients whose primary payer was Medicare FFS, and I assume that any physician who sees Medicare patients—which I identify from MD-PPAS—is available to see any Medicare beneficiary in the markets where he or she practices. I further restrict choice sets to only include physicians living closer than the 97.5th percentile distance between any patient and any chosen physician's primary practice location, about 70 miles.

Table 3 reports summary statistics for important variables from the patients' perspective. Each variable is first calculated at the level of the choice set. Then the mean, standard deviation, minimum, and maximum are taken across choice sets. The average patient is choosing from about 40 orthopedic surgeons. Even though only 38.9 percent of hip and knee replacement surgeons have ever been sued in Florida, the average hip/knee replacement patient is choosing from a set of physicians where 54.9 percent have been sued.

5 Methods

I model the demand for physician services under a discrete choice framework. Consistent with the literature on estimating demand for health care services, the consumer agent is a physician–patient pair, and I am agnostic as to how the decision-making power between the two is split (*See* Grennan et al. 2022; Baker, Bundorf, and Kessler 2016). Recent research into patient hospital and procedure choice suggests that physicians seem to play a more dominant role in the decision-making process (Baker, Bundorf, and Kessler 2016). That said, patients do not need a referral to see a specialist under traditional Medicare, and I am not able to identify referrals or their absence with the HIF.

The indirect utility to patient–physician consumer pair i of seeing treating physician j in market m and time t is given by

$$u_{ijmt} = Malpractice'_{jt}\beta + \gamma' PSI\_Rate_{jt} + X'_{ijmt}\delta + \epsilon_{ijmt} \tag{1}$$

where $Malpractice_{jt}$ is a vector describing the physician's malpractice history at time t, PSI_Rate_{jt} is the rate of PSI-flagged per $1,000$ at-risk patients as described above, X_{ijmt} is a vector of other physician and physician–patient characteristics, and ϵ_{ijmt} is a mean-zero term for unobservable, idiosyncratic utility terms. As is standard practice, I assume that ϵ_{ijmt} follows a type-I extreme value distribution, resulting in the familiar choice probability

$$P_{ijmt} = \frac{e^{Malpractice'_{jt}\beta + \gamma' PSI\_Rate_{jt} + x'_{ijmt}\delta}}{\sum_{k=1}^{K} e^{Malpractice'_{kt}\beta + \gamma' PSI\_Rate_{jt} + X'_{ikmt}\delta}} \tag{2}$$

where P_{ijmt} is the probability of patient–referrer pair i choosing to see specialist j in market

m and quarter t. Note in Equation (2) the absence of a 1 in the denominator. Given the context and the data I have available, there is no plausible outside option to consider. As a result, I estimate the relative, instead of the absolute, demand for physician services. This is not a significant concern for my purposes.

The primary explanatory variables of interest in this study belong to the vector $Malpractice_{jt}$. I consider several versions of this vector. In the simplest version, I estimate this model using an indicator for whether the physician has ever been sued and had that lawsuit reported to the PLCR prior to quarter t.

I also use specifications that include indicators for whether a physician has been sued once, twice, thrice, or four or more times. Figure 2 plots the distribution of the number of times a surgeon has ever been sued and shows why this specification is appropriate. As discussed below, I separately estimate versions of my alternate specifications where the malpractice variables are limited to the previous four years. For those specifications, I include indicator variables for being sued once or two or more times. Most physicians have not been sued in the past four years, a minority have been sued once in the past four years, and a very small number have been sued twice or more in the past four years. Using these specifications allows me to see how demand responds to the number of times a physician has been sued while looking to see if there are any nonlinearities in the effect of number of suits on demand.

I use time relative to being reported to the PLCR because the easiest and most certain way to know whether a physician has been sued for malpractice in Florida is to query the PLCR. A prospective patient or physician may or may not hear about an incident of malpractice through rumors or media reports. The patient or physician may be able to check court records for lawsuits against a specialist, but that often requires paying for a background check service or visiting a courthouse in person. Some counties—but not all—maintain searchable online records, and the counties that do maintain these databases do not all use the same service or vendor. By contrast, if anyone has any interest in querying the PLCR, they can do so with ease and for free. According to the Internet Archive's WayBackMachine, the URL for the PLCR's medical malpractice search portal has been active since at least May 6, 2006, so patients and physicians would have been able to access it during the sample period.

To address some measure of the severity of a physician's malpractice history, I also include the sum of all damages paid as a settlement or award in all suits prior to quarter t. In any one case, damages capture the likelihood that the doctor fell short of the standard of care and the extent of the injuries to the patient. The higher the damages, the more likely it is that a physician erred or the more serious the injury or both.

Admittedly, damages capture these values with some degree of noise. Risk preferences, litigation dynamics, and even the law can cause damages to diverge from the ideal value of $Damages_{ij} = \mathbb{1}\{Negligent_j\} * Injury_i$, where $\mathbb{1}\{Negligent_j\} = 1$ if and only if physician j was professionally negligent and $Injury_i$ is the amount of patient i's injury. Even that idealized value of $Damages_{ij}$ may not perfectly proxy for the magnitude of the physician's error. For example, under the "eggshell plaintiff rule," a defendant found to have been negligent is responsible for the full extent of a plaintiff's injuries, even if a typical person would not have been injured as badly. As a result, a doctor who commits a small error that nonetheless causes very grievous injuries will be liable for larger damages than a doctor who commits a more serious mistake but whose patient fortuitously manages to sustain smaller injuries. However, this scenario is only likely to be problematic if the size of the damages is uncorrelated with the size of the error—for example, if there are a lot of eggshell plaintiffs—which is unlikely. While damages are a crude proxy for the degree of physician error, they are a proxy nonetheless.

Temporal proximity likely affects how much patients and referring physicians weight any aspect of a specialist physician's malpractice history. That a doctor was sued for malpractice 16 years ago, for example, probably makes less of a difference than that same doctor having been sued for malpractice a few months ago. Indeed, when constructing their claims-free discount programs, insurers often make some discount available to doctors with no claims in the past three to five years and the full discount available in the past ten to fifteen years.[5] Accordingly, I estimate specifications where $Malpractice_{jt}$ only includes the number of suits and maximum damages paid out in the last few years. As a preliminary matter, I estimate models that use one to seven years as lookback periods. I keep the maximum lookback period length at seven years so that the same period can be used for both the malpractice variables and for the PSIs. For reasons set forth below, I ultimately settle on four years for my primary specifications.

The vector X_{ijmt} contains several variables that are important components of the demand for physician services. Given its documented importance to patient demand, I include distance between patient i's zip code and the primary practice location of physician j. Consistent with the literature, I include distance as a cubic expression to account for the decreasing marginal disutility of distance (Gutacker et al. 2016; Moscelli et al. 2016). I also include physician gender, a quadratic of physician tenure, and the physician's patient volume in the previous three years. Since I have individual-level data, I estimate the demand model in Equation (1) via maximum likelihood.

To make the results more directly interpretable, I report two transformations of the utility parameter estimates. The first is simply the average marginal effect of each characteristic z_j on physician demand, calculated by taking the marginal effect of each component

$$\frac{\partial P_{ij}}{\partial z_j} = \frac{\partial u_{ijmt}}{\partial z_j} P_{ijmt}(1 - P_{ijmt}) \tag{3}$$

and averaging over the sample (Train 2009). The second transformation is the willingness to travel WTT, defined as

[5] The exact number of years varies between insurers.

$$\left.\frac{d\,dist_{ijt}}{d\,z_{jt}}\right|_{\widetilde{dist}} = -\left.\frac{\partial u_{ijmt}/\partial z_{jt}}{\partial u_{ijmt}/\partial dist_{ijt}}\right|_{\widetilde{dist}} = -\frac{\beta_z}{\delta_1^{dist} + 2\delta_2^{dist}\widetilde{dist} + 3\delta_3^{dist}\widetilde{dist}^2} \tag{4}$$

where $\widetilde{dist}$ is the average distance between the patient and the chosen physician, z_{jt} is the physician characteristic in question, and β_z is the marginal utility parameter associated with that characteristic as identified from estimating Equation (1) (Gutacker et al. 2016; Moscelli et al. 2016).

I further explore two additional possible mechanisms for reputational harm: being reported to the NPDB and having one's malpractice history reported on one's Florida Department of Health (DOH) online practitioner profile. Both outcomes involve a damages threshold—a physician is reported to the NPDB if there is an award or settlement greater than \$0 and her practitioner profile on the DOH's website lists all cases with a settlement or award greater than $\$100,000$ in the past ten years.[6] I therefore impute that a malpractice lawsuit has been reported to the NPDB if the damages paid in that lawsuit are positive; if they are \$0, I infer that the case has not been reported to the NPDB. Similarly, I infer that a case is listed on a doctor's online DOH profile in quarter t if the damages are greater than $\$100,000$ and the case resolved 40 or fewer quarters ago. To reflect the fact that actual payment of a settlement or award is what triggers malpractice insurers' and the DOH's reporting requirements, I modify the timing to be relative to the final disposition of the suit instead of relative to being reported to the PLCR. I then run analyses similar to those above where I use a simple indicator variable, number of reports, and damages involved. Because the DOH website listing requirements already include a specific lookback period, I do not include any time limits when estimating these models.

[6] Fla. Stat. Ann. § 456.041.

6 Results

6.1 Primary Results

Tables 4 and 5 report the utility parameter estimates and average marginal effects for Equation (1) with no time restriction on physician j's malpractice history. For both tables, Column (1) presents the estimates for the specification with an indicator for whether specialist j was ever sued and Column (2) presents the estimates for total damages. Column (3) reports estimates when $Malpractice_{jt}$ is a set of indicators for having been sued once, twice, three times, or four or more times. The specification for Column (4) is the same as for Column (3) with total damages included. In Table 5, the average marginal effect of each physician characteristic is on the probability of being selected and is reported in percentage points. For example, the first entry of Column (1) indicates that a physician who has ever been sued is 0.256 percentage points less likely to be selected for a knee or hip replacement surgery than one who has not.

All of the estimates in Tables 4 and 5 are intuitively signed or at least consistent with prior research. Patient utility—and a physician's probability of being chosen—is decreasing in number of past lawsuits, total damages, rate of PSI events, and distance, and it is less for doctors who have been sued compared to those who have not. The estimates of $Tenure$ and $Tenure^2$ in Table 4 imply that utility is a concave function in tenure, and utility is maximized when a physician has been practicing for about 27.3 years. Because patient utility is maximized with respect to tenure roughly in the middle of the distribution—median physician tenure in my sample is 22 years—I omit tenure from the average marginal effects in Table 5. Consistent with previous research, (Sarsons 2017; Zeltzer 2020), there appears to be a significant penalty for female physicians.

Of most importance for this study, the estimates for having ever been sued, number of lawsuits, and total damages are all negative and statistically significant. A physician who has been sued is 0.256 percentage points less likely to be selected for a knee or hip replacement surgery than one who has never been sued. This is a modest effect size, but it is somewhat large relative to the average fitted probability of being selected (2.476 percentage points) and quite large relative to the median fitted probability of being selected (0.986 percentage points). The probability of being selected is increasing in number of lawsuits—a physician sued twice is less likely to be selected than a doctor sued once, and so on—but nonlinearly. The biggest drop in probability of being selected occurs at a physician's first lawsuit. The average marginal effect of being sued is much larger than that of an additional $\$10,000$ in total damages.

6.2 Time-Restricted Models

6.2.1 Choice of Lookback Period Length

As a preliminary matter, I estimate versions of the models with "ever sued" and "total damages," each separately for various lookback period lengths. Specifically, I estimate these models with lookback periods of one to seven years. Figures 4 and 5 report these estimates.

Starting with Figure 4, the estimates for ever sued are negative and statistically significant for all choices of lookback period length. Starting from a period of one year, the estimates become more negative and appear to stabilize at around -0.146 with a 4-year lookback period. The estimates for total damages follow a similar pattern. Figure 5 shows that estimates for total damages become increasingly negative until four years, when they stabilize at -0.0079. The most likely reason for this common pattern is that it takes time for information to disseminate about a lawsuit. Because shorter lookback periods allow for more years of observations, Figures 4 and 5 would suggest that a four-year lookback is most appropriate.

6.2.2 Time-Restricted Results

Tables 6 and 7 report the estimates for Equation (1) when $Malpractice_{jt}$ is limited to malpractice claims reported to the PLCR in the 16 quarters prior to quarter t. These results are very similar to the time unrestricted estimates, with only a few meaningful differences. Most notably, Columns (3) and (4) of Tables 6 and 7 only include indicators for having been sued once or twice or more. This is because relatively few physicians have been sued in the past four years. Fewer still have been sued more than once, let alone three or four times.

At first glance, it would appear that having been sued in the last four years matters less for patient demand than having been sued at any time in the past, but this is not quite right. Table 7 indicates that an orthopedic surgeon sued in the past four years is 0.19 percentage points less likely to be chosen than one who has not, compared with the 0.256 percentage point reduction noted above. But, note that the average number of lawsuits conditional on having ever been sued (without time restrictions) is 1.98, and the estimate for having been sued twice (again, without time restrictions) is -0.242. Similarly, note that the average number of lawsuits in the last four years conditional on having been sued in the past four years is 1.25, and the estimate for ever sued in the previous four years in Table 7 Column (1) is . This is not only very close to the estimate for one lawsuit in Column Table 7 (3) , but both are very close to the estimate for one lawsuit without time restrictions in Table 5. The estimates for two lawsuits with and without time restrictions are also very close. Taken together, it appears that “ever sued” mostly just captures number of lawsuits, and these effects do not seem to change based on how recent the malpractice lawsuits were.

6.3 Willingness to Travel

Tables 8 and 9 report the results in terms of willingness to pay. Each estimate indicates the number of miles a patient would be willing to travel to see a doctor with one more unit of the characteristic in question. Negative (positive) estimates mean that patients are willing to travel farther to avoid (seek out) that characteristic. So a patient would be willing to travel 1.887 miles to avoid an orthopedic surgeon who has ever been sued in favor of one who has not. For context, this is about the same distance that patients would travel to avoid seeing a female physician and farther than they would be willing to travel to avoid seeing a physician with one more PSI event per $1,000$ at-risk patients (the average PSI rate per $1,000$ at-risk patients in the sample is 2.38). The average distance travelled to a physician that a patient actually saw is 15.32 miles.

6.4 Alternative Reputational Mechanisms

Finally, Tables 10–13 report the utility parameter, average marginal, and WTT estimates for models when one assumes that the mechanism by which a patient or referring physician learns of a knee/hip surgeons malpractice history is the DOH practitioner profile website or the NPDB. The estimates for these alternative models are generally smaller than those of the primary results. However, they are all of roughly the same magnitude, and almost all are statistically significant and of the same sign—with the exception of total damages for the DOH model with the full specification, which is neither.

7 Conclusion

Previous studies have shown that the prospect of being sued for medical malpractice leads physicians to alter their behavior and practice so-called defensive medicine. However, the reason for physicians' sensitivity to being sued remains unclear. We know that physicians are not financially exposed to their own malpractice. Indeed, even meritorious lawsuits almost always settle for less than the policy claim maximum, and medical malpractice insurance rates are only minimally affected by additional lawsuits. We also know that physicians being sued only lose approximately 2.7-5 days of work to malpractice lawsuits.

Other scholars have postulated that physicians may be motivated by concerns of reputational loss from being sued. However, no previous study has examined whether medical malpractice lawsuits do, in fact, cause reputational loss among physicians. This paper attempts to fill that gap by treating changes in demand for physician services as a proxy for reputational loss. Specifically, this paper asks whether being sued for medical malpractice actually results in a loss of demand from patients and referring physicians.

I find that patients and referring physicians view specialists with more extensive malpractice histories more negatively and are less likely to choose them for a knee or hip replacement surgery. Overall, these findings represent mixed evidence in favor of the reputational harm hypothesis.

On the one hand, the effects I observe, while statistically significant, are economically quite modest. By way of illustration, consider an orthopedic surgeon who has been sued three times for $\$40,000$ each. Using the more complete specification from Column (4) of Table 5, that physician would be 0.26 percentage points (10.62 percent) less likely to be selected than a physician who had never been sued. Patients would be willing to travel 1.79 miles (11.68 percent) farther to avoid seeing this doctor.

Note that these are likely upper bounds on the effect sizes. Outside of Florida it is not likely that a patient or referring physician would have access to this much information about a physician's malpractice history. In addition, if this hypothetical surgeon's malpractice insurance carrier were the Doctors Company, then as long as those three suits were paid out in separate years, his malpractice insurance premium would not increase.

On the other hand, there are several aspects of my findings that might nonetheless cause physicians to be wary of these otherwise small effects. For one thing, it only takes one lawsuit before a physician experiences the biggest drop in demand for her services. Moreover, this loss of demand does not fade away over time. Lastly, patients and referring physicians do not seem to care whether a doctor prevails—by winning their case and paying out $0 or by settling for a nominal value—because they do not place much weight on damages. Returning to the hypothetical, if the physician above won every case brought against him and therefore paid out $0, then he would only be 0.03 percentage points more likely to be selected.

8 References

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Tables

Table 1: Summary Statistics for Knee and Hip Replacement Surgeons

	Mean	SD	Min	Max
Ever Sued	0.39	0.49	0.00	1.00
Number of Suits	0.77	1.33	0.00	15.00
Total Damages ($10,000s)	8.57	26.93	0.00	416.50
Ever Sued (Previous 4 Years)	0.12	0.33	0.00	1.00
Number of Suits (Previous 4 Years)	0.15	0.45	0.00	5.00
Total Damages ($10,000s, Previous 4 Years)	1.84	9.79	0.00	259.20
PSI Rate Per 1000 at-risk Patients	2.38	2.63	0.00	36.92
Tenure	22.88	10.75	2.00	57.00
Female Physician	0.14	0.35	0.00	1.00

Note:
These figures represent summary statistics for knee and hip replacement surgeons in Florida as of their last quarter present in the sample period (2011–14).

Table 2: Summary Statistics by Sued Status

	Ever Sued		Never Sued		
	Mean	SD	Mean	SD	p.Value
PSI Rate Per 1000 at-risk Patients	2.28	2.28	2.45	2.82	0.68
Patient Volume (Previous 4 Years)	1358.72	1977.23	1050.07	1313.51	0.01
Tenure	27.33	9.07	20.04	10.77	<.01
Female Physician	0.07	0.26	0.19	0.39	<.01
N	767.00		1203.00		

Table 3: Summary Statistics for Knee and Hip Replacement Patients' Choice Sets

	Mean	SD	Min	Max
Number of Doctors	40.31	20.64	1.00	86.00
Proportion of Doctors Sued (All Time)	0.55	0.09	0.00	1.00
Proportion of Doctors Sued (Previous 4 Years)	0.12	0.10	0.00	0.67
Average Number of Suits (All Time)	1.24	0.37	0.00	5.00
Average Number of Suits (Previous 4 Years)	0.16	0.14	0.00	0.71
Avg. Tot. Damages (All Time, $10,000s)	12.27	5.58	0.00	145.50
Avg. Tot. Damages (Previous 4 Years)	1.68	1.60	0.00	12.11
Average PSI Rate (Per 1000 At-Risk	1.49	0.86	0.00	5.45
Average Distance to Doctor	26.03	11.00	0.00	64.29
Minimum Distance to Doctor	5.39	6.53	0.00	61.98
Maximum Distance to Doctor	52.93	16.81	0.00	70.06
Average Tenure	24.63	1.85	16.20	41.00
Number of Female Physicians	1.29	1.43	0.00	11.00

Note:
Each variable statistic is first calculated at the level of the choice set. Then the mean, standard deviation, minimum, and maximum are taken across choice sets. For physician characteristics, the mean therefore represents an average of the characteristic weighted by how many knee and hip replacement patients live in the markets served by the physician.

Table 4: Utility Parameter Estimates (No Time Limits)

	(1)	(2)	(3)	(4)
Ever Sued	−0.2070***			
	(0.0084)			
Total Damages ($10,000s)		−0.0035***		−0.0020***
		(0.0002)		(0.0002)
1 Lawsuit			−0.1570***	−0.1471***
			(0.0105)	(0.0105)
2 Lawsuits			−0.1953***	−0.1649***
			(0.0117)	(0.0121)
3 Lawsuits			−0.2609***	−0.1883***
			(0.0162)	(0.0177)
≥ 4 Lawsuits			−0.3472***	−0.2266***
			(0.0161)	(0.0200)
PSIs Per 1000 At-Risk Patients	−0.1291***	−0.1260***	−0.1253***	−0.1263***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Patient Volume (100s, Prv 4 Years)	0.0260***	0.0254***	0.0262***	0.0260***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Female Physician	−0.2057***	−0.2043***	−0.2147***	−0.2115***
	(0.0275)	(0.0275)	(0.0276)	(0.0276)
Tenure	0.0413***	0.0340***	0.0404***	0.0406***
	(0.0022)	(0.0021)	(0.0022)	(0.0022)
Tenure^2	−0.0008***	−0.0007***	−0.0007***	−0.0007***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Distance	−0.1116***	−0.1116***	−0.1120***	−0.1119***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Distance^2	−0.0002**	−0.0002*	−0.0002**	−0.0002**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance^3	<0.0001***	<0.0001***	<0.0001***	<0.0001***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
N	70418	70418	70418	70418
McFadden Pseudo R2	0.165	0.165	0.165	0.165
Nagelkerke Pseudo R2	0.689	0.689	0.69	0.69

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:
This table presents estimates for models where the malpractice history variables are not time limited

Table 5: Average Marginal Effects (No Time Limits)

	(1)	(2)	(3)	(4)
Ever Sued	−0.2563***			
	(0.0105)			
Total Damages ($10,000s)		−0.0044***		−0.0025***
		(0.0002)		(0.0003)
1 Lawsuit			−0.1943***	−0.1822***
			(0.0130)	(0.0130)
2 Lawsuits			−0.2418***	−0.2042***
			(0.0145)	(0.0150)
3 Lawsuits			−0.3230***	−0.2331***
			(0.0201)	(0.0220)
$\geq$ 4 Lawsuits			−0.4299***	−0.2805***
			(0.0200)	(0.0248)
PSIs Per 1000 At-Risk Patients	−0.1598***	−0.1559***	−0.1551***	−0.1563***
	(0.0039)	(0.0039)	(0.0039)	(0.0040)
Patient Volume (100s, Prv 4 Years)	0.0321***	0.0315***	0.0324***	0.0322***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Female Physician	−0.2547***	−0.2529***	−0.2658***	−0.2618***
	(0.0340)	(0.0341)	(0.0341)	(0.0341)
Distance	−0.1308***	−0.1305***	−0.1310***	−0.1309***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:
Estimates represent average marginal effects expressed in percentage points.

Table 6: Utility Parameter Estimates (4-Year Lookback)

	(1)	(2)	(3)	(4)
Ever Sued	−0.1538***			
	(0.0113)			
Total Damages ($10,000s)		−0.0074***		−0.0050***
		(0.0006)		(0.0007)
1 Lawsuit			−0.1457***	−0.0976***
			(0.0126)	(0.0141)
$\geq$ 2 Lawsuits			−0.1799***	−0.0743**
			(0.0215)	(0.0255)
PSIs Per 1000 At-Risk Patients	−0.1281***	−0.1271***	−0.1280***	−0.1276***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Patient Volume (100s, Prv 4 Years)	0.0255***	0.0254***	0.0255***	0.0255***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Female Physician	−0.2076***	−0.2055***	−0.2073***	−0.2087***
	(0.0275)	(0.0275)	(0.0275)	(0.0275)
Tenure	0.0341***	0.0324***	0.0340***	0.0337***
	(0.0022)	(0.0021)	(0.0022)	(0.0022)
Tenure^2	−0.0007***	−0.0007***	−0.0007***	−0.0007***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
Distance	−0.1116***	−0.1115***	−0.1116***	−0.1115***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Distance^2	−0.0002*	−0.0002*	−0.0002*	−0.0002*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance^3	<0.0001***	<0.0001***	<0.0001***	<0.0001***
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)
N	70418	70418	70418	70418
McFadden Pseudo R2	0.164	0.164	0.164	0.164
Nagelkerke Pseudo R2	0.687	0.687	0.687	0.687

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

This table presents estimates for models where the malpractice history variables are limited to the four years preceding patients' choice.

Table 7: Average Marginal Effects, (4-Year Lookback)

	(1)	(2)	(3)	(4)
Ever Sued	−0.1904***			
	(0.0139)			
Total Damages ($10,000s)		−0.0092***		−0.0062***
		(0.0007)		(0.0008)
1 Lawsuit			−0.1804***	−0.1209***
			(0.0155)	(0.0174)
$\geq$ 2 Lawsuits			−0.2228***	−0.0920**
			(0.0266)	(0.0316)
PSIs Per 1000 At-Risk Patients	−0.1585***	−0.1573***	−0.1584***	−0.1579***
	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Patient Volume (100s, Prv 4 Years)	0.0316***	0.0315***	0.0316***	0.0316***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Female Physician	−0.2570***	−0.2544***	−0.2566***	−0.2584***
	(0.0340)	(0.0340)	(0.0340)	(0.0341)
Distance	−0.1305***	−0.1304***	−0.1305***	−0.1305***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:
Estimates represent average marginal effects expressed in percentage points.

Table 8: Willingness to Travel for Physician Characteristics (No Time Limits)

	(1)	(2)	(3)	(4)
Ever Sued	−1.8870***			
	(0.0772)			
Total Damages ($10,000s)		−0.0323***		−0.0184***
		(0.0015)		(0.0019)
1 Lawsuit			−1.4291***	−1.3407***
			(0.0955)	(0.0960)
2 Lawsuits			−1.7782***	−1.5025***
			(0.1068)	(0.1102)
3 Lawsuits			−2.3752***	−1.7154***
			(0.1481)	(0.1616)
$\geq$ 4 Lawsuits			−3.1611***	−2.0644***
			(0.1473)	(0.1825)
PSIs Per 1000 At-Risk Patients	−1.1770***	−1.1520***	−1.1411***	−1.1506***
	(0.0296)	(0.0296)	(0.0297)	(0.0297)
Patient Volume (100s, Prv 4 Years)	0.2366	0.2323	0.2383	0.2368
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Female Physician	−1.8755***	−1.8678***	−1.9548***	−1.9267***
	(0.2508)	(0.2517)	(0.2511)	(0.2514)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

This table presents estimates for models where the malpractice history variables are not time limited

Standard errors, reported in parentheses, are calculated using the delta method.

Table 9: Willingness to Travel for Physician Characteristics (4-Year Lookback)

	(1)	(2)	(3)	(4)
Ever Sued	−1.406***			
	(0.103)			
Total Damages ($10,000s)		−0.068***		−0.046***
		(0.005)		(0.006)
1 Lawsuit			−1.333***	−0.893***
			(0.115)	(0.129)
$\geq$ 2 Lawsuits			−1.645***	−0.680**
			(0.196)	(0.234)
PSIs Per 1000 At-Risk Patients	−1.172***	−1.163***	−1.170***	−1.167***
	(0.030)	(0.030)	(0.030)	(0.030)
Patient Volume (100s, Prv 4 Years)	0.233	0.233	0.233	0.233
	(0.003)	(0.003)	(0.003)	(0.003)
Female Physician	−1.898***	−1.880***	−1.895***	−1.908***
	(0.252)	(0.252)	(0.252)	(0.252)

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Note:
This table presents estimates for models where the malpractice history variables are limited to the four years preceding patients' choice.
Standard errors, reported in parentheses, are calculated using the delta method.

Table 10: Utility Parameter Estimates for DOH Website as Reputational Mechanism

	(1)	(2)	(3)	(4)
Ever Sued	−0.1155***			
	(0.0109)			
Total Damages ($10,000s)		−0.0034***		0.0005
		(0.0002)		(0.0004)
1 Lawsuit			−0.0405***	−0.0524***
			(0.0116)	(0.0153)
$\geq$ 2 Lawsuits			−0.4854***	−0.5266***
			(0.0263)	(0.0439)
PSIs Per 1000 At-Risk Patients	−0.1262***	−0.1262***	−0.1251***	−0.1251***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Patient Volume (100s, Prv 4 Years)	0.0253***	0.0253***	0.0252***	0.0252***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Female Physician	−0.2000***	−0.1948***	−0.1703***	−0.1692***
	(0.0275)	(0.0275)	(0.0276)	(0.0276)
Tenure	0.0330***	0.0330***	0.0329***	0.0329***
	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Distance	−0.1116***	−0.1117***	−0.1121***	−0.1121***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
N	70418	70418	70418	70418
McFadden Pseudo R2	0.164	0.164	0.164	0.164
Nagelkerke Pseudo R2	0.687	0.687	0.688	0.688

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:
These models also include a quadratic term for tenure and distance and a cubic term for distance.

Table 11: Utility Parameter Estimates for NPDB as Reputational Mechanism

	(1)	(2)	(3)	(4)
Ever Sued	−0.1244***			
	(0.0092)			
Total Damages ($10,000s)		−0.0036***		−0.0027***
		(0.0002)		(0.0003)
1 Lawsuit			−0.0543***	−0.0155
			(0.0105)	(0.0111)
≥2 Lawsuits			−0.2538***	−0.0887***
			(0.0138)	(0.0203)
PSIs Per 1000 At-Risk Patients	−0.1248***	−0.1264***	−0.1240***	−0.1254***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Patient Volume (100s, Prv 4 Years)	0.0253***	0.0252***	0.0253***	0.0252***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Female Physician	−0.2041***	−0.1962***	−0.1935***	−0.1947***
	(0.0275)	(0.0275)	(0.0275)	(0.0275)
Tenure	0.0338***	0.0341***	0.0324***	0.0338***
	(0.0021)	(0.0021)	(0.0021)	(0.0022)
Distance	−0.1118***	−0.1116***	−0.1116***	−0.1117***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
N	70418	70418	70418	70418
McFadden Pseudo R2	0.164	0.164	0.164	0.165
Nagelkerke Pseudo R2	0.687	0.688	0.688	0.688

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:
These models also include a quadratic term for tenure and distance and a cubic term for distance.

Table 12: WTT Estimates for DOH Website as Reputational Mechanism

	(1)	(2)	(3)	(4)
Ever Sued	−1.0553***			
	(0.0992)			
Total Damages ($10,000s)		−0.0312***		0.0047
		(0.0022)		(0.0039)
1 Lawsuit			−0.3705***	−0.4790***
			(0.1057)	(0.1400)
$\geq$ 2 Lawsuits			−4.4352***	−4.8112***
			(0.2409)	(0.4006)
PSIs Per 1000 At-Risk Patients	−1.1530***	−1.1546***	−1.1431***	−1.1425***
	(0.0296)	(0.0296)	(0.0296)	(0.0296)
Patient Volume (100s, Prv 4 Years)	0.2308	0.2315	0.2306	0.2305
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Female Physician	−1.8275***	−1.7828***	−1.5564***	−1.5462***
	(0.2514)	(0.2518)	(0.2522)	(0.2523)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:

Standard errors, reported in parentheses, are calculated using the delta method.

Table 13: WTT Estimates for NPDB as Reputational Mechanism

	(1)	(2)	(3)	(4)
Ever Sued	-1.1359^{***}			
	(0.0836)			
Total Damages (\$10,000s)		-0.0327^{***}		-0.0250^{***}
		(0.0016)		(0.0024)
1 Lawsuit			-0.4960^{***}	-0.1420
			(0.0956)	(0.1013)
$\geq$ 2 Lawsuits			-2.3160^{***}	-0.8105^{***}
			(0.1258)	(0.1857)
PSIs Per 1000 At-Risk Patients	-1.1399^{***}	-1.1555^{***}	-1.1317^{***}	-1.1453^{***}
	(0.0296)	(0.0296)	(0.0296)	(0.0297)
Patient Volume (100s, Prv 4 Years)	0.2312	0.2303	0.2308	0.2303
	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Female Physician	-1.8632^{***}	-1.7937^{***}	-1.7656^{***}	-1.7789^{***}
	(0.2513)	(0.2515)	(0.2513)	(0.2515)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note:
Standard errors, reported in parentheses, are calculated using the delta method.

Figures

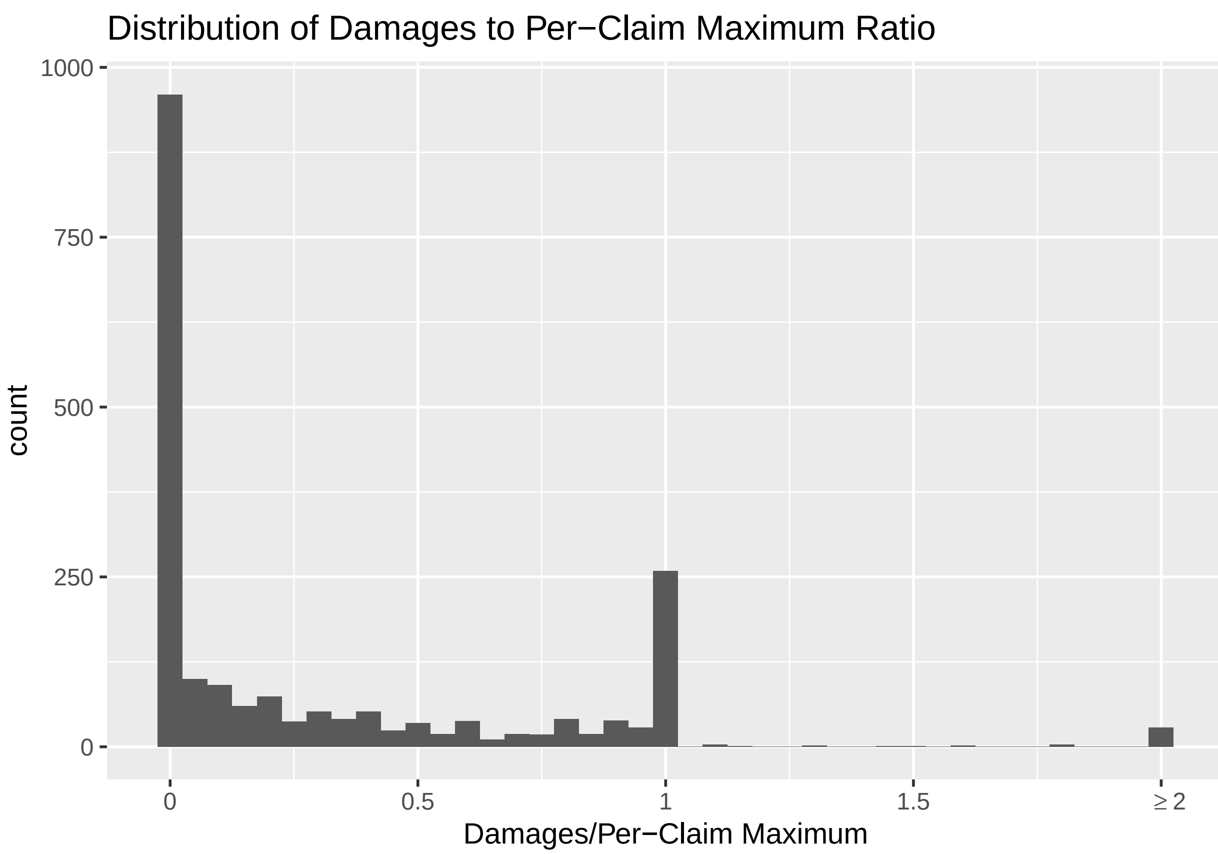

Figure 1: This figure shows the distribution of the ratio of damages paid (after a jury award or negotiated settlement) to the per-claim maximum in the defendant-physician's insurance policy.

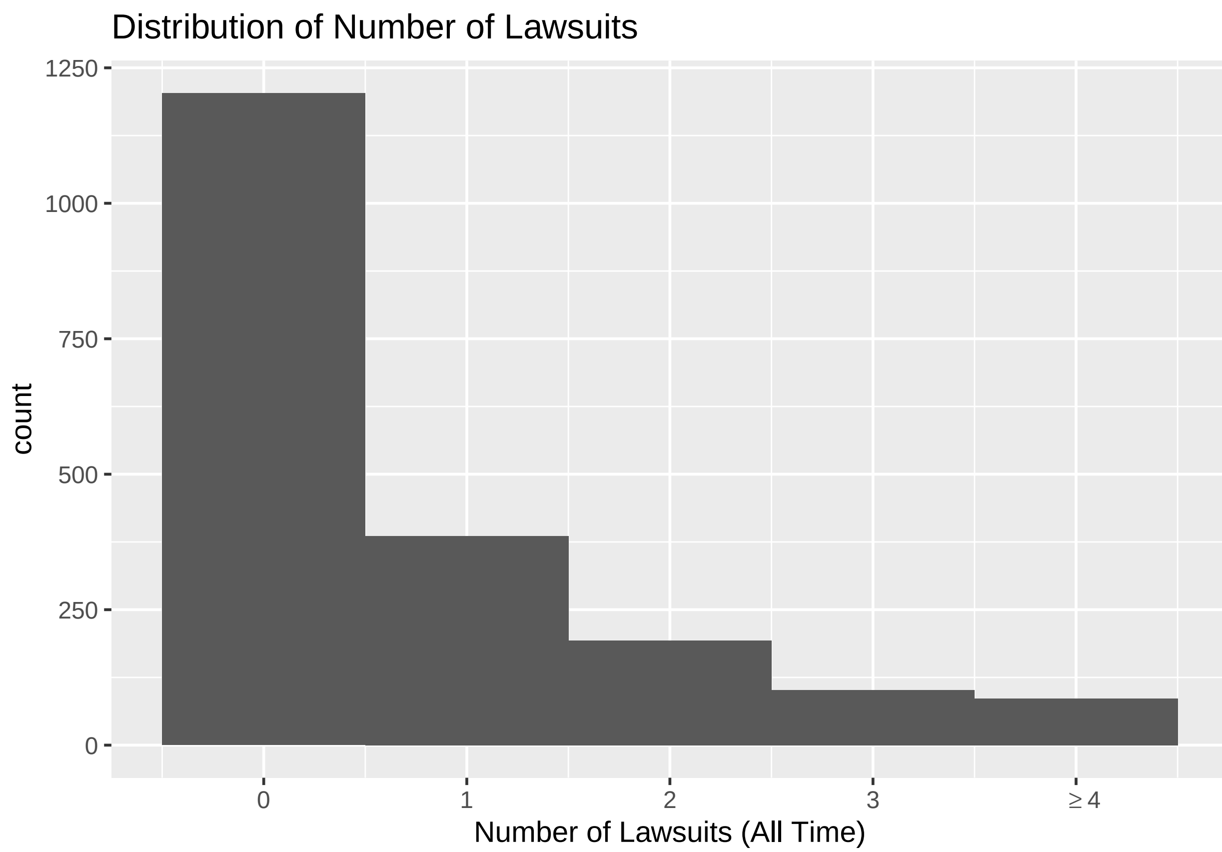

Figure 2: Distribution of the number of times physicians have been sued. For each physician, this value is taken from the last quarter they appear in the sample.

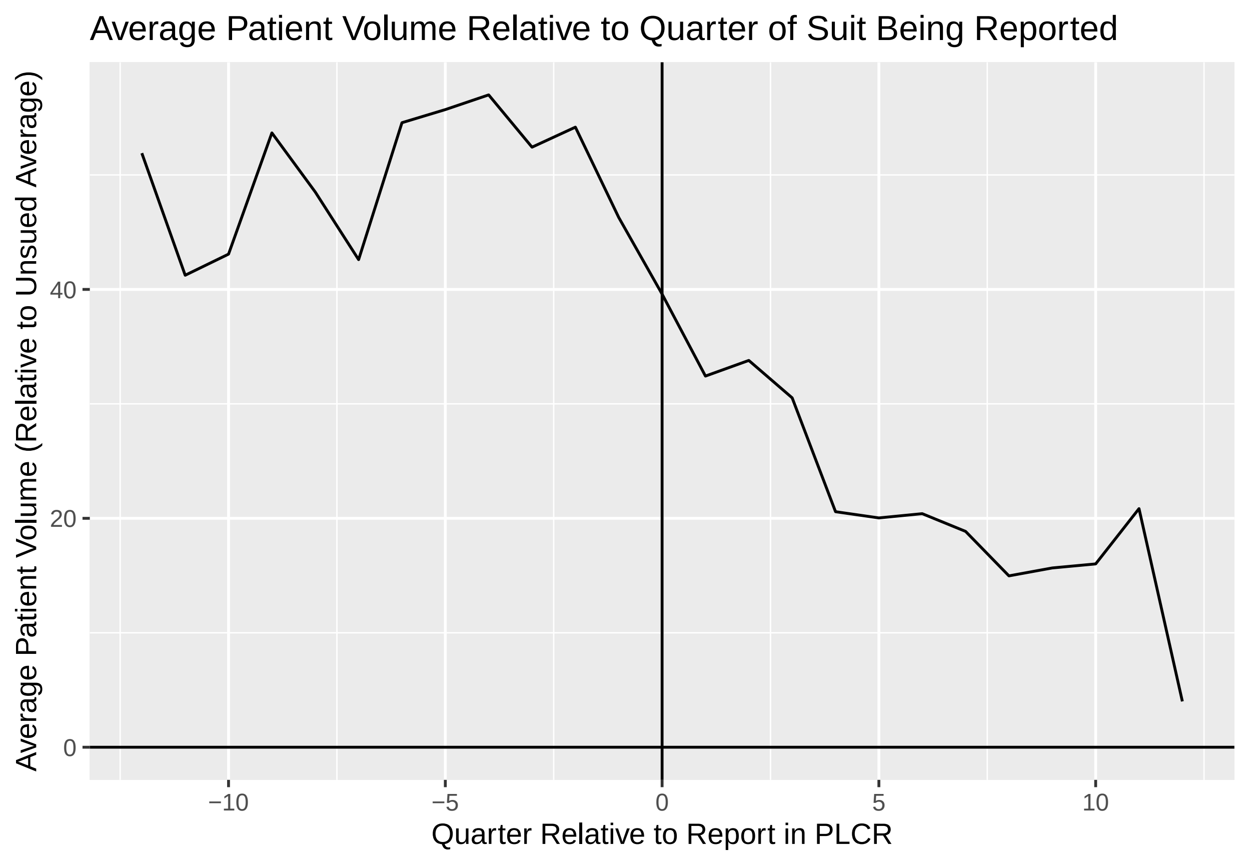

Figure 3: Time series of average patient volume for sued physicians relative to the quarter their lawsuit was reported in the PCLR. The y-axis is the difference between the average patient volume for sued physicians in that relative quarter and the average patient volume for physicians that are not sued, taken over the entire sample period.

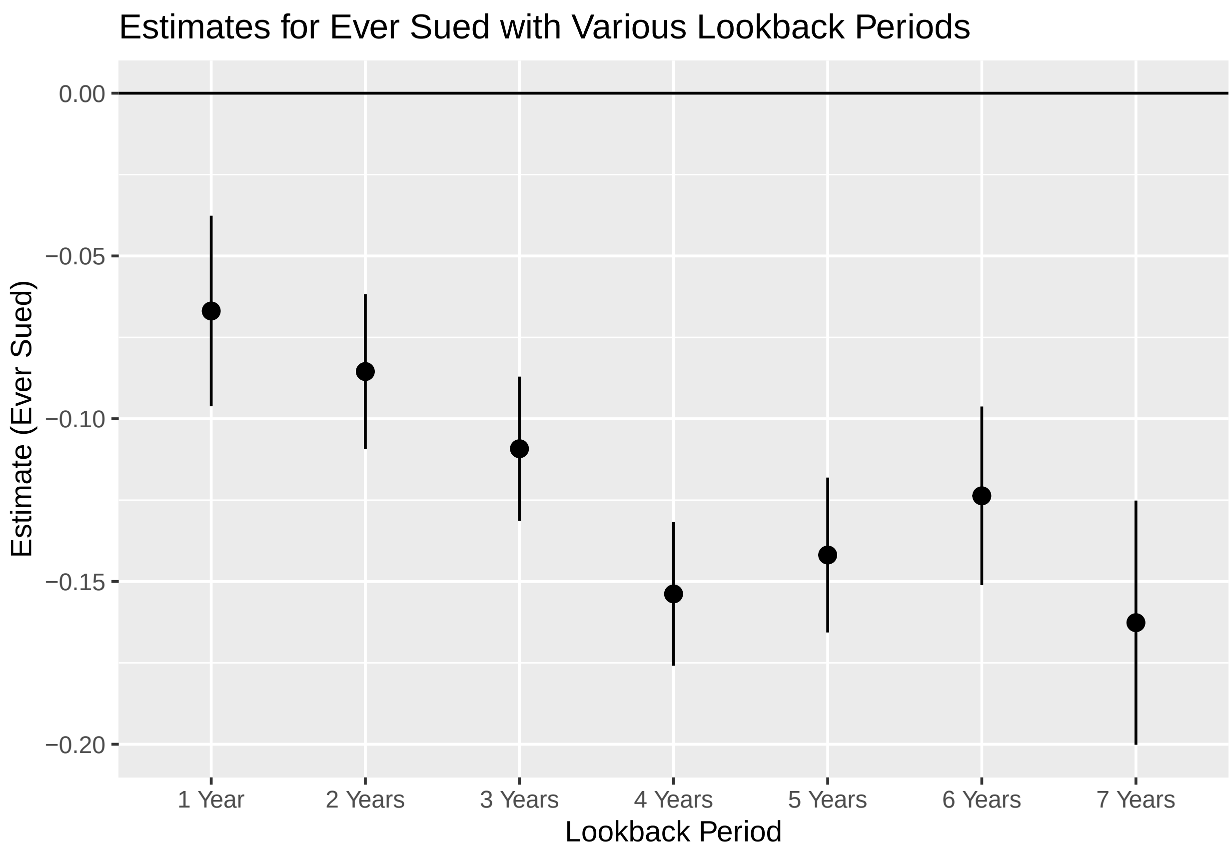

Figure 4: Estimates for "Ever Sued" for various lookback period lengths. Lookback period lengths vary from one to seven years.

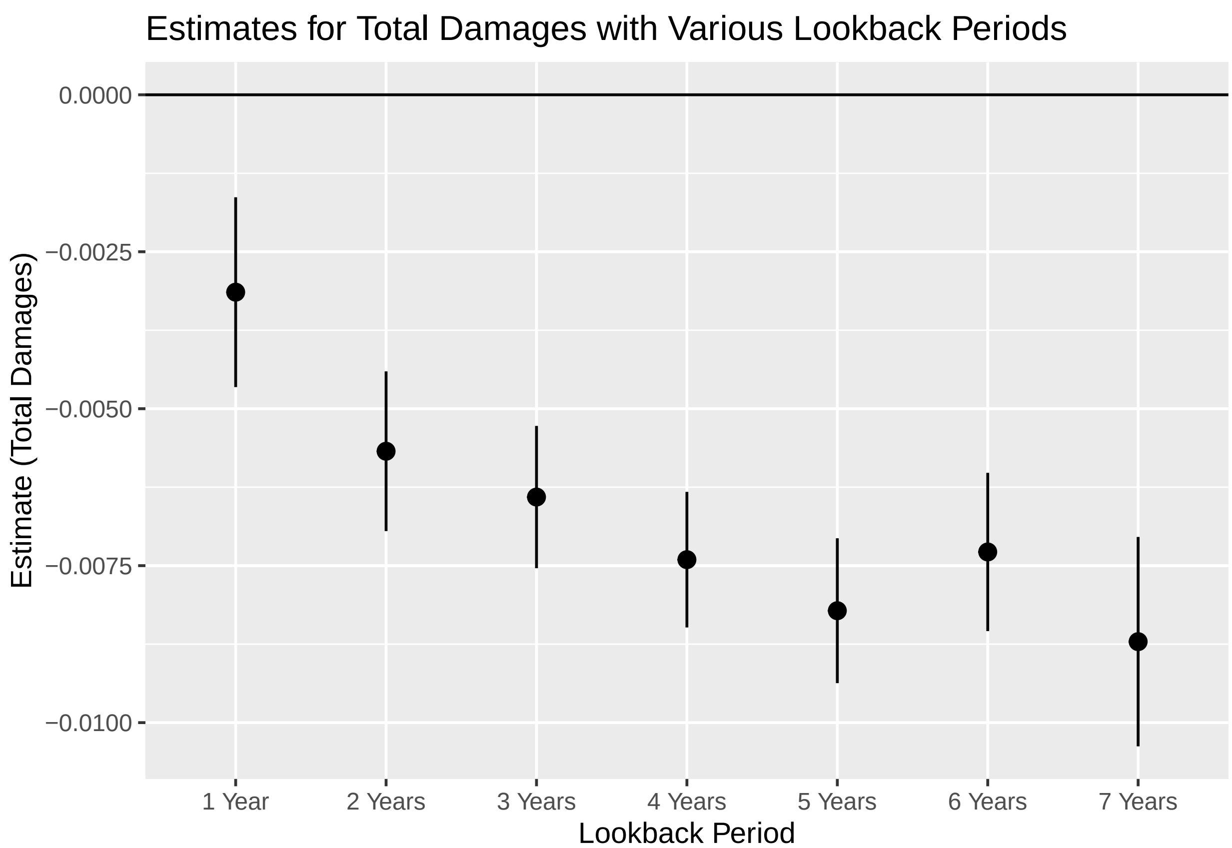

Figure 5: Estimates for "Total Damages" for various lookback period lengths. Lookback period lengths vary from one to seven years.

Appendix

In this appendix, I show the sensitivity of my results to various alternative definitions of practicing 'in' a geographic market in a given quarter and various alternative distance limits. Figures present the parameter estimates for the key malpractice variables—ever sued, total damages, and one, two, three, and four or more suits—when various threshold numbers and percentages are applied to define whether a physician practices in a geographic market in a quarter. Threshold numbers are distinguished by color and threshold percentages are distinguished by shape. The primary specification—doctors are considered as practicing in a market in a quarter if they treat 5 or more patients constituting 5 or more percent of their practice—is indicated in each figure.

For each parameter, all estimates are negative, statistically significant, and have relatively similar magnitudes and standard errors. Most of the variation between estimates appears to be driven by the different threshold numbers of patients, rather than threshold percentages. Looking at the 'ever sued' parameter, the estimate from my primary specification is very similar to the estimates for all definitions of 'practicing in' when the threshold number of patients is 1, 3, 5, or 10. The estimates get more negative when the threshold number of patients is 20, and more negative still when the threshold is 30. The difference between the average estimate when the threshold is 5 patients and when the threshold is 30 patients is -0.12, or about 0.57 percent of the average parameter estimate for the 5-patient threshold. In terms of average marginals, this translates to a roughly 5-fold increase in the effect size. However, in absolute terms this is the difference between being 0.2 and 1.1 percentage points less likely to be chosen.

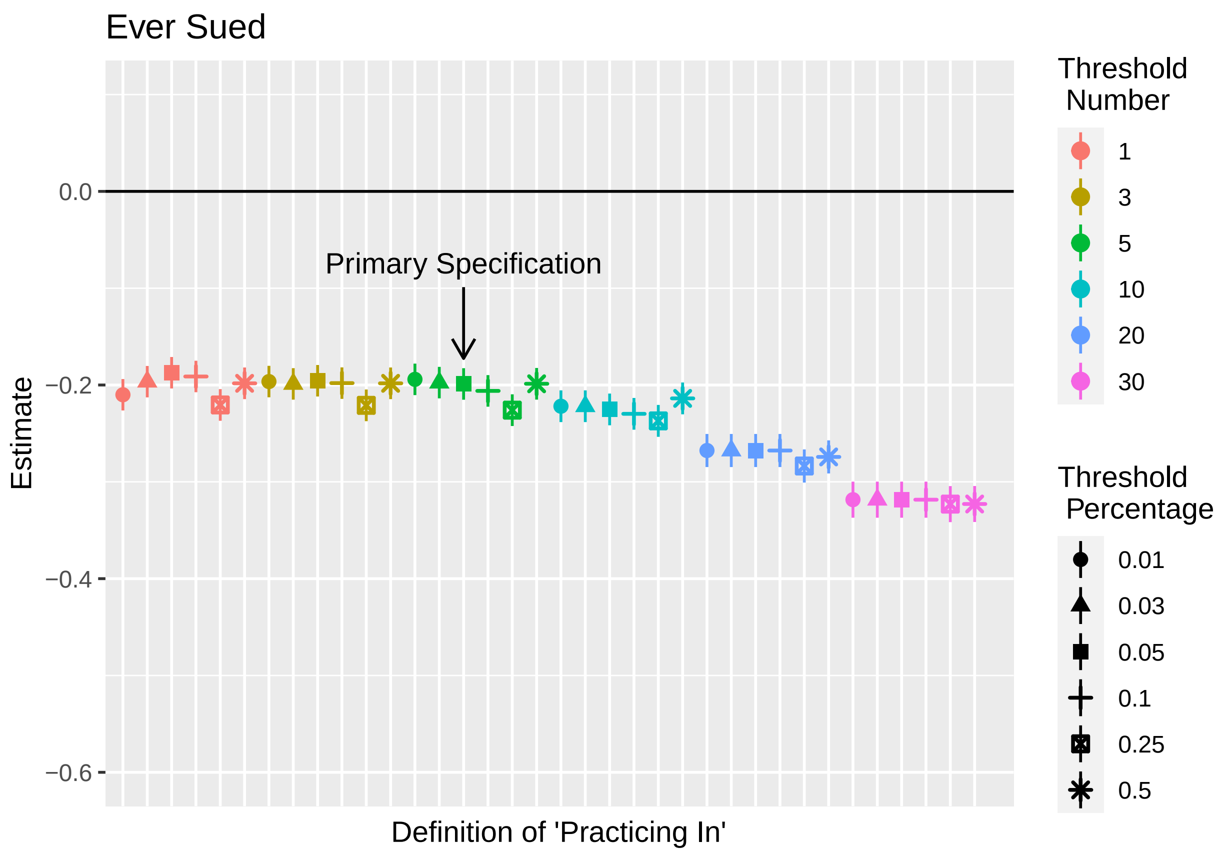

Figure A1: Parameter estimates for "Ever Sued" under various number and percentage thresholds for practicing "in" a market.

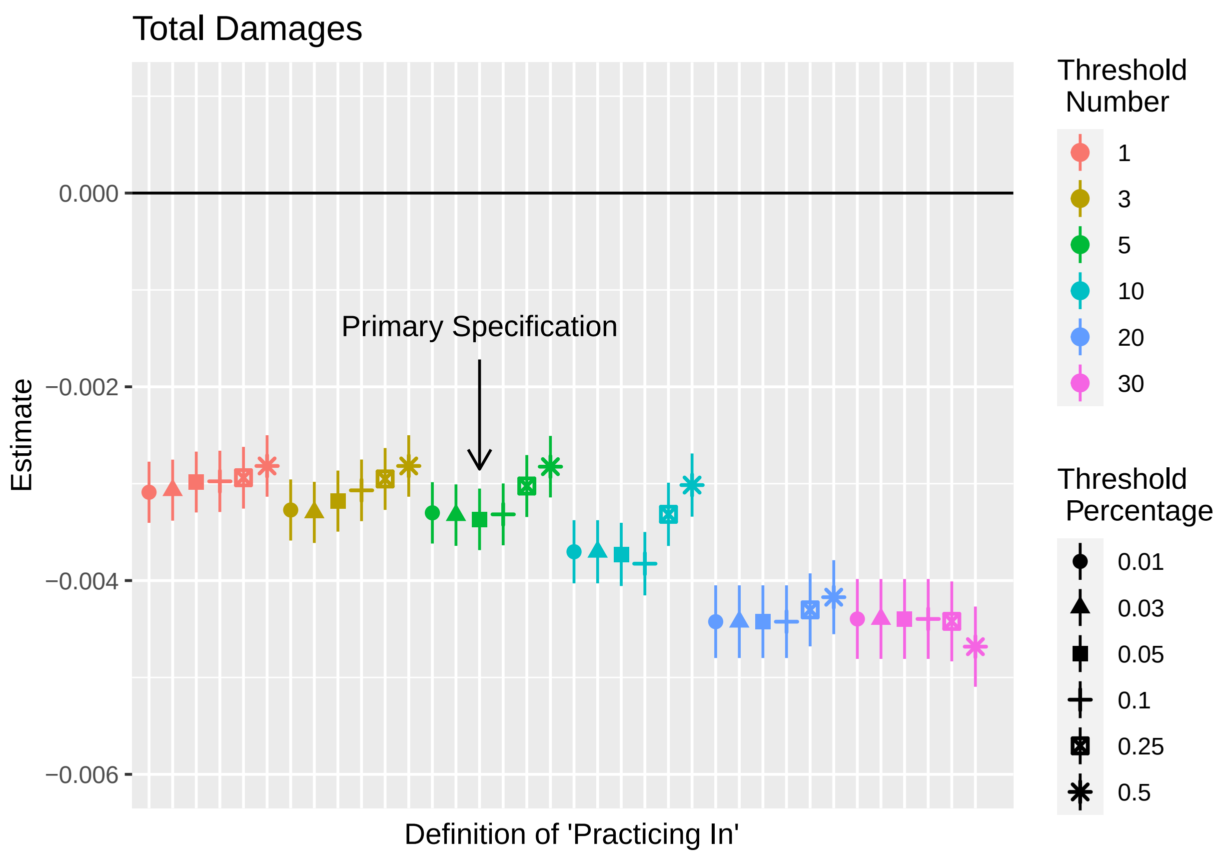

Figure A2: Parameter estimates for “Total Damages” under various number and percentage thresholds for practicing “in” a market. Because of the very small size of these estimates, the y-axis for this figure is one tenth the size as the y-axes for the other figures.

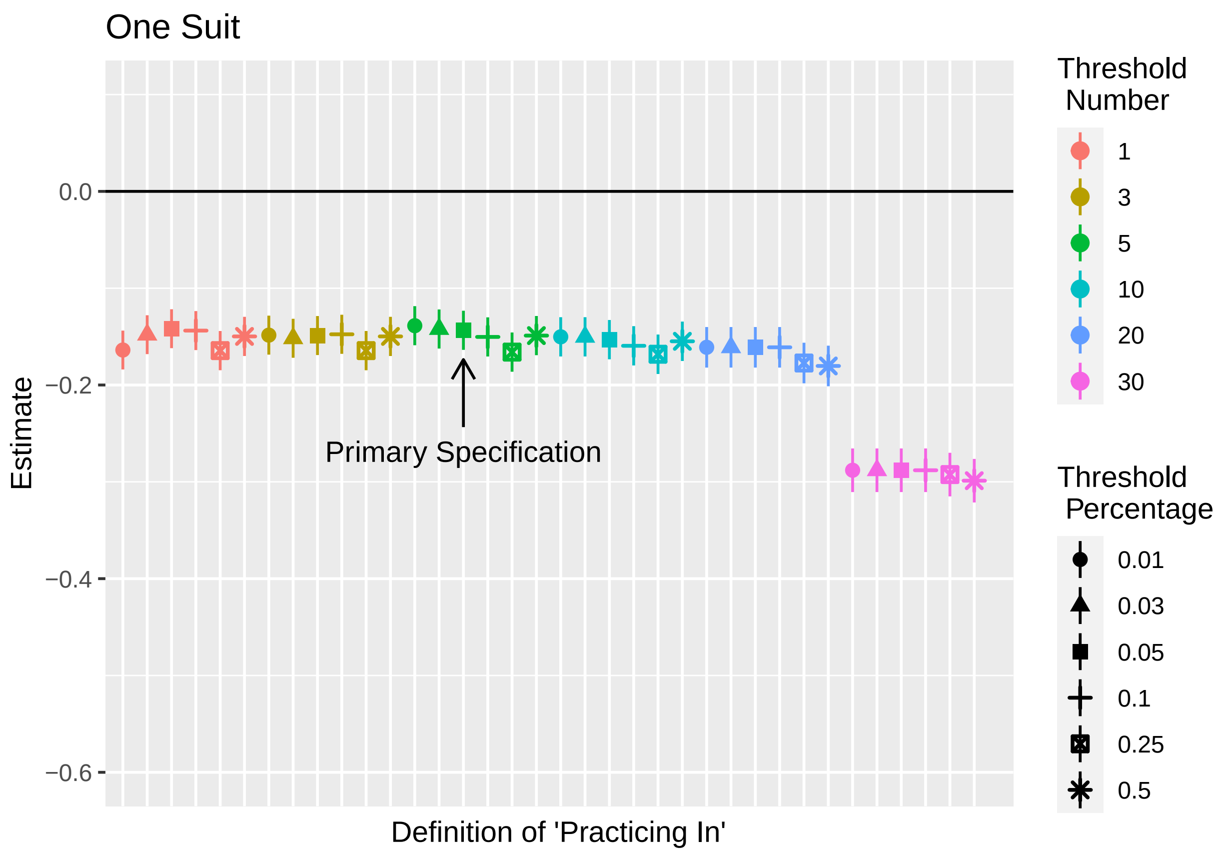

Figure A3: Parameter estimates for “One Suit” under various number and percentage thresholds for practicing “in” a market.

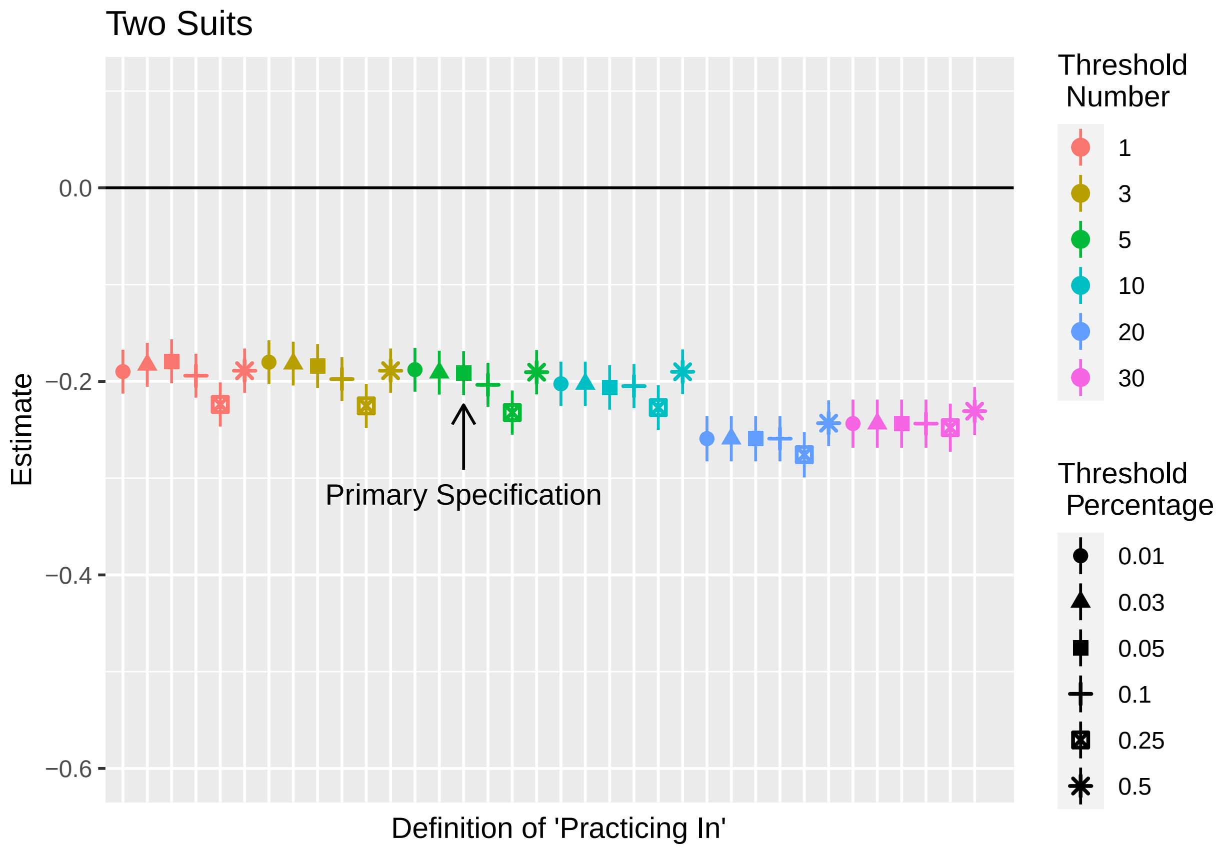

Figure A4: Parameter estimates for “Two Suits” under various number and percentage thresholds for practicing “in” a market.

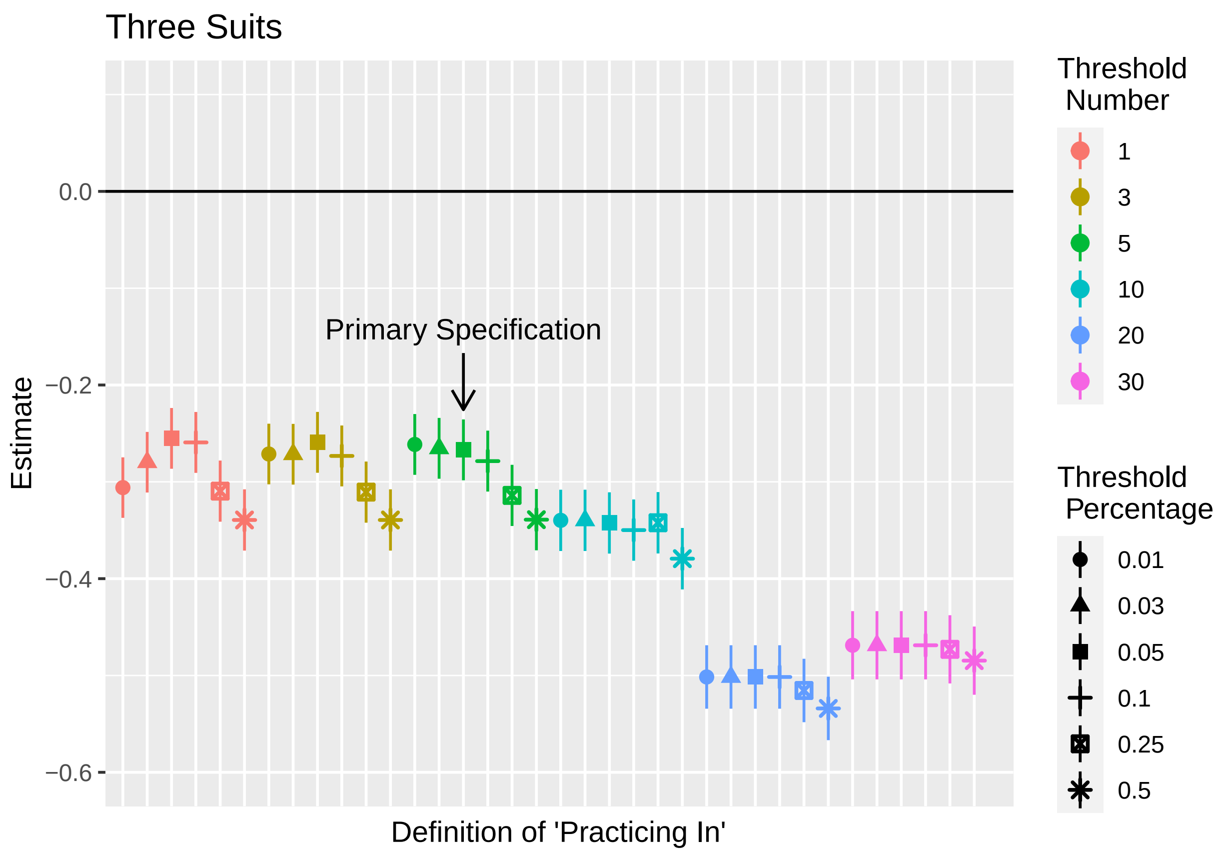

Figure A5: Parameter estimates for “Three Suits” under various number and percentage thresholds for practicing “in” a market.

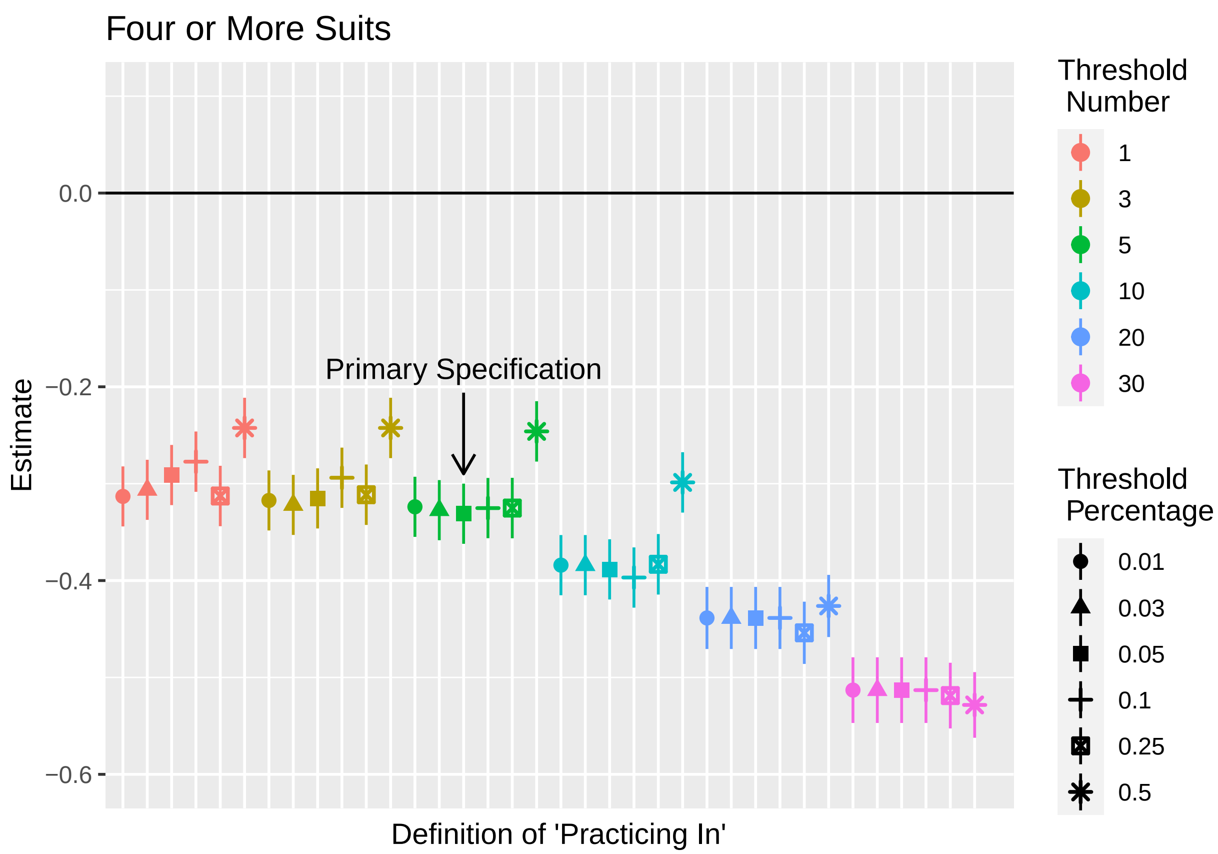

Figure A6: Parameter estimates for “Four or More Suits” under various number and percentage thresholds for practicing “in” a market.