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The Impact of Liability on the Physician Labor Market

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Abstract

This study examines the impact of malpractice reforms on physician behavior using a new measure of liability risk and a nationally representative, individual-level data set on physician behavior. We match our liability measure to data on physician behavior from the Physician Practice Costs and Income Survey (PPCIS). Data from the PPCIS bracket a period of substantial state-level legal reform between 1983 and 1988, which provides identifying variation in our liability measure. We estimate the impact of liability reform on hours worked. We find an estimated elasticity of hours worked to liability exposure of −.285 for the full sample of physicians. The effect for physicians ages 55 or older is much larger: we find an elasticity of −1.224 for this category. We find that an increase in $1 of expected liability is associated with a $.70–$1.05 increase in malpractice premiums.

1. Introduction

Medical malpractice reform is the subject of ongoing debate among academics and policy makers. Critics of the current system point to several flaws. First, it does a poor job of identifying and compensating victims of negligent injury (Harvard Medical Practice Study 1990; Studdert and Brennan 2000). Second, its high administrative costs are not justified by estimates of deterrence (Kessler and McClellan 1996, 2002a). Third, it creates inefficiencies in the practice of medicine. One aspect of the potential inefficiency is commonly referred to as defensive medicine: actions taken by physicians (or other health care providers) meant to reduce the probability of a malpractice lawsuit. Examples include

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ordering an excessive number of diagnostic tests or performing medical procedures of dubious value to a patient. By engaging in such behavior, physicians plausibly reduce the risk of a litigation claim, at the cost of an inefficient use of resources.

Perhaps the most well-known empirical economic papers on this topic are by Kessler and McClellan (1996, 2002a), who examine how health expenditures for Medicare recipients vary with changes in state liability reforms. They find that up to 9 percent of expenditures on treatment for heart disease and heart attacks can be attributed to excessive care due to physicians practicing defensive medicine.[1] In contrast, other studies of defensive medicine find different results. For example, Sloan et al. (1995) and the Congressional Budget Office (2004) find little effect of liability reform on expenditures, while Dubay, Kaestner, and Waidmann (1999, 2001) find a small effect on cesarean section procedures attributable to liability reform.

A related literature examines how malpractice liability affects physicians' labor market participation. For example, Klick and Stratman (2007) examine the impact of liability reform on the number of physicians practicing in a given state. In a similar vein, Kessler, Sage, and Becker (2005), Encinosa and Hellinger (2005), and Matsa (2007) find that physician labor supply increases when states adopt caps (direct reforms in Kessler, Sage, and Becker [2005]) limiting liability.[2] In addition, there is substantial anecdotal evidence of physicians leaving particular specialties because of liability concerns, which has fueled political attempts to institute malpractice litigation reform (see, for example, U.S. House 2003).

Our paper explores the link between liability risk and physicians' hours of work. Although most analyses focus on the extensive margin—for example, the choice of specialty and the choice of whether to practice at all—it is possible that we might observe some action on the intensive margin as well. This could have implications for access to health care beyond the widely publicized physician exits observed in some specialties: a large number of physicians working shorter hours could have equilibrium effects of the same magnitude as physician exits.

Previous research has assumed that because medical malpractice premiums are not experience rated, liability is essentially a fixed cost and hence changes in liability will not affect labor supply directly unless it is to induce more effort to cover the fixed cost (Thornton 1997). Yet a theoretical link between labor supply and liability risk is simple to establish: Suppose a risk-averse physician chooses an optimal number of patients to maximize the expected utility of profits and faces a liability risk that is a function of the number of patients treated. If liability insurance is available but does not fully cover potential losses, then an

[1] Kessler and McClellan (2002a) find an impact on costs of around 4 percent when controls for managed care are included in the regression.

[2] Mello et al. (2006) take a different approach, estimating malpractice liability premiums on physician labor supply, and find some evidence of an effect. Thornton (1997), using the 1983 version of the Physician Practice Costs and Income Survey (PPCIS), finds a positive impact of medical malpractice premiums on labor supply.

exogenous increase in the liability risk has an ambiguous effect on the number of patients treated.[3] The intuition behind the ambiguous result is straightforward and arises because an increasing risk of liability has two effects. First, it increases the marginal cost of treating a patient, thereby reducing the incentive to take on additional patients. Second, it reduces expected income, thereby making the treatment of an additional patient more valuable in expected utility terms. Which of these effects dominates is theoretically uncertain. It is important to note that this model contrasts sharply with the view that malpractice premiums fully insure all potential losses from malpractice litigation. With this framework, physicians have an incentive to avoid actions that will increase potential liability costs even when paying malpractice premiums.

A key innovation of our paper is a new measure of liability that allows us to exploit variation in liability risk across states and physician specialties. The measure is based on a combination of the Florida closed-claim file, which contains data on all malpractice awards in the state of Florida, and the National Association of Insurance Commissioners (NAIC) data on malpractice claims for all states from 1980 to 1988. Most previous work uses binary variables to measure the impact of malpractice reform, but such variables mask considerable statutory variation across states.[4] For example, on one extreme, Nebraska instituted a cap of $1.25 million on total damages, economic and noneconomic. In contrast, its neighboring state, Kansas, instituted a cap of $250,000 on noneconomic awards only. The conventional binary-variable approach treats both states the same, which seems likely to miss important differences in outcomes. States also vary widely in their underlying liability risk, so the same nominal cap on malpractice awards may represent very different experiments in different states. Finally, different physician specialties vary greatly in their exposure to liability, and hence their changes in liability risk can be markedly different when caps are imposed or changed.

We develop our measure of the impact of changes in law in a given state on a specific specialty's expected liability cost. Next we combine our liability measure with a nationally representative, individual-level data set of physicians, the Physician Practice Costs and Income Survey (PPCIS, 1983 and 1988). The data include physician work hours and income, among other variables. These surveys bracket a period of substantial state-level reform, which provides the major source of identification in our empirical strategy. Of the 34 states that enacted caps by 2002, 14 did so between 1983 and 1988.

We find an estimated elasticity of hours worked with respect to liability exposure of $-.285$ for the full sample of physicians. The interpretation is that a

[3] Lawthers et al. (1992) find that the average physician lost between 3 and 5 days of practice defending a malpractice suit and that 6 percent of physicians incurred some out-of-pocket expenses.

[4] Two important exceptions are Kessler and McClellan (2002b), who use data from closed medical malpractice claims to capture liability exposure, and Bhattacharya (2005), who estimates the impact of the probability of a lawsuit on specialty choice and income.

10 percent increase in expected liability costs (not necessarily malpractice premiums) is associated with a 2.85 percent decrease in hours worked per week. The effect for physicians ages 55 or older is much larger: we find an elasticity of -1.224 for this category. We also examine the link between our pure liability measure and malpractice premiums. We find that an increase of $1 in expected liability is associated with a $.70–$1.05 increase in malpractice premiums.

2. Data Description

We use three primary data sources; two are combined to construct our liability measure. We describe each of the data sources and then turn to the creation of the liability measure.

2.1. Data on Physician Behavior: The Physician Practice Costs and Income Surveys

We use two cross-sectional surveys: the 1983 and 1988 PPCIS. The 1983 PPCIS is a survey of physicians conducted by National Opinion Research Center under contract to the Health Care Financing Administration. The survey includes responses from 4,729 physicians (out of 6,847 eligible) drawn from a stratified random sample of physicians from the American Medical Association's (AMA's) 1984 Physician Master File. The physicians were asked numerous detailed questions regarding practice costs, pricing policies, and work schedules. The data set also contains variables concerning the physicians' personal characteristics (age, sex, specialty, and the like) obtained from the AMA Physician Master File. The survey took place over a period of 9 months, from October 1984 to June 1985. The 1988 PPCIS is a similar cross-sectional study, with 3,505 participating physicians (a 61 percent response rate), which was conducted between July 1989 and March 1990.

The PPCIS cross sections have two primary strengths for our research purposes: First, the timing of the surveys is very useful because they bracket many of the important state-level medical liability reform measures during the 1980s. Second, the data contain a rich set of behavioral and practice characteristics. We have information on both income and work hours, as well as information on case mix and practice costs.

These data on intensive-margin behaviors contrast with other studies examining the link between liability and physician behavior that focus on the extensive margin—physician entry, exit, and relocation decisions (see Klick and Stratmann 2007; Kessler, Sage, and Becker 2005; Matsa 2007). Unfortunately, the PPCIS lacks information that would allow careful analysis of the extensive margin—it does not include retired physicians, part-time physicians (under 20 hours a week), or those employed only by a health maintenance organization, hospital, clinic, or medical school (including clinical or research fellows), and so we view our work as complementary to this other set of studies.[5,6]

2.2. The Florida Closed-Claim File

To estimate the impact of limitations on damages on a physician's expected liability, we need to know the distribution of awards facing each specialty. Although this information does not exist in every state, Florida has maintained a database of all medical malpractice claims from 1975 to the present. In 1980, insurance companies began reporting more comprehensive information to the Florida Department of Insurance, and data on physician specialty were added.[7] These data are unique in providing a specialty-specific distribution of medical malpractice claims over an extended period of time. As outlined below, we use claims filed before 1987 as a baseline for the distribution of state-level malpractice claims. These cases predate any limitation on noneconomic damages in Florida and, regardless of the period of resolution, are not covered by subsequent restrictions. We treat these as the distribution of potential payments resulting from actions taken by the physician in the sample period. One feature of this approach is that we capture claims resolved years after the sample period. The three most recent claims in the data were resolved in 1999.[8]

Using these data, we could treat all specialties as if they face the same liability risk as Florida and simply truncate the distribution at the level of the cap enacted in a particular state. Simply truncating judgments that are over the cap is consistent with the reality of trials. With few exceptions, juries are not told about the existence of caps: awards are generally reduced to the cap after the verdict is entered. More problematic is how to treat settlements. Over 93 percent of the cases that are not unilaterally dropped by the plaintiff end in settlement. Moreover, plaintiffs win around 30 percent of the trials. Given the small number of cases that go to trial and result in payment, we are unable to estimate the liability measure for each specialty using only cases that end in a trial. Our solution is

[5] Despite the data screen inherent in the survey, a few physicians are included who may actually be working part time. Because we do not want these observations to influence the results, we focus on physicians likely to be working full time by restricting the age range to physicians older than 30 and younger than 75 who had an income of at least $35,000 in the previous year. The results are not materially affected by the restriction.

[6] A related point is that the PPCIS restricts its sample to those physicians whom Kessler, Sage, and Becker (2005) identify as mostly exposed to the cost of liability, specifically those in non-group-practice settings (that is, those not employed solely by a health maintenance organization and hospital or government employees). We do not view this as a limitation since, as Kessler, Sage, and Becker point out, this is the population of interest when evaluating the impact of liability on physician labor supply.

[7] See Helland, Klick, and Tabarrok (2005) for a more detailed discussion of these data.

[8] One concern is that this long tail might be driving the results. For this reason, we also estimated the model using only claims paid before 1987 and found similar results.

to truncate all payments at the cap as described below.[9] This approach has an important failing in that it ignores the fact that states differ dramatically in their liability risk. For this reason, we need to construct an overall liability risk to shift the Florida distribution of awards before imposing the cap.

2.3. The National Association of Insurance Commissioners Data on State Malpractice Claims

To account for variation across states in the level of malpractice claims, we use the National Association of Insurance data on malpractice claims by insurer in each state by year. These data do not include specialty information, so they do not provide the level of detail of the Florida closed-claim file. But they do allow us to scale the Florida data to account for differences in litigation costs across states. The data include both incurred losses for the year and actual losses paid. We use incurred losses to construct the liability measure.[10]

2.4. Description of Liability Index

A key aspect of our analysis is the construction and use of a measure of liability. Ideally, we would like to have a measure of all liability awards by specialty, state, and year. With such a measure, we could directly evaluate the change in liability risk as various state-level regulations are modified. However, such data are not available, and so, as an alternative, we outline a methodology that allows us to create an index across all states and specialties, using the Florida closed-claim data and the NAIC data.

2.4.1. Theoretical Justification

Our key assumption is that the unrestricted distribution of claims within a given specialty is similar across all states, up to a factor of proportionality, γ^S. Specifically, let $f(x|c)$ be the probability density function of liability awards, x, conditional on specialty, c, in a given state in which γ^S is normalized to one. Assuming a continuous distribution, the conditional mean for specialty c is represented by

$$E[x|c] = \int_0^\infty xf(x|c)dx. \tag{1}$$

Suppose that liability awards by specialty are proportional across states. Let y

[9] There are models of settlement negotiation that would accord well with this approach. For example, Priest and Klein (1984) model litigation as a game in which the value of the case is known to both parties but litigants diverge in their assessment of the likelihood of victory at trial. In their model, trials are errors, but the value of the case is unaffected by trial or settlement.

[10] See Born and Viscusi (1998) for a more extensive discussion of these data.

be the claims in state S. Using the change-of-variables technique, we have the following:

$$y = \gamma^S x, \qquad \gamma^S > 0,$$

so

$$\begin{aligned} x &= (1/\gamma^S)y, \\ dx &= (1/\gamma^S)dy, \end{aligned} \tag{2}$$

and

$$f(y) = f_x(y/\gamma^S)(1/\gamma^S);$$

so

$$E[y|c] = \int_0^\infty yf(y|c)dy = \int_0^\infty \gamma^S x f_x(x|c)dx = \gamma^S E[x|c].$$

Therefore, the expected liability for specialty c in state S is proportional to the mean in the reference state. For our analysis, we want to examine how liability changes with a cap on liability awards. To compute the mean with a cap in state S, we have

$$\begin{aligned} E[y|c,\ \text{cap} = \overline{Y}] &= \int_0^{\overline{Y}} yf(y|c)dy + \overline{Y}\int_{\overline{Y}}^\infty f(y|c)dy, \\ &= \int_0^{\overline{Y}/\gamma^S} \gamma^S x f(x|c)dx + \overline{Y}\int_{\overline{Y}/\gamma^S}^\infty f(x|c)dx. \end{aligned} \tag{3}$$

If we had a measure of γ^S, we could estimate this mean with data from the reference state, as well as the mean without the cap.[11] Our liability measure can therefore be expressed as follows:

$$\text{liability}_{s,k,t} = \begin{cases} \gamma^s E[x|\text{specialty} = k,\ \text{state} = \text{FL}] & \text{when state } s \text{ has no cap} \\ \displaystyle\int_0^{\overline{Y}^S/\gamma^s} \gamma^s x f(x|k,\ \text{FL})dx + \overline{Y}^S \int_{\overline{Y}^S/\gamma^s}^\infty f(x|k,\ \text{FL})dx & \text{when state } s \text{ has a cap.} \end{cases} \tag{4}$$

[11] We implicitly assume that caps have no effect on the distribution of claims, $F(.|.)$. It is plausible that the institution of caps reduces the distribution for claims to the level of the cap for claims that would have otherwise exceeded the cap, but that change would not affect the computation of our index in equation (4). Our method makes the stronger assumption that caps do not affect the distribution of claims for amounts less than the cap, an assumption that is untestable with our data but seems reasonable.

2.4.2. Estimation of γ^S

The NAIC gathers data on all claims paid by insurance in each state. Let $y_{s,i,t}$ be the average claim per physician and $p_{s,i,t}$ be the number of physicians in specialty s, state i, and year t. Then total claims in state i and year t can be written as

$$c_{i,t} = \sum_s p_{s,i,t} y_{s,i,t}. \tag{5}$$

In the NAIC data, we observe only $c_{i,t}$, not the individual components. However, suppose that claims are proportional to claims in Florida, our reference state: $y_{s,i,t} = \gamma^S y_{s,\mathrm{FL},t}$. Then we would have

$$c_{i,t} = \gamma^S \sum_s p_{s,i,t} y_{s,\mathrm{FL},t}. \tag{6}$$

The term γ^S could then be estimated as

$$\gamma^S = \frac{c_{i,t}}{\sum_s p_{s,i,t} y_{s,\mathrm{FL},t}}, \tag{7}$$

where the numerator is the NAIC state estimate for liability claims in state i and year t and the denominator is the weighted average of the Florida specialty claims where the weighting is the state- and year-specific measure of doctors in each specialty. Intuitively, we remove any difference in liability risk across states that may be due to the differences in the population of physicians practicing in that state. We estimate γ for each state using all years from 1980 to 1986 during which a state does not have a cap in place. The estimates range from a high of 3.40 in New York to a low of .17 in South Carolina.

2.4.3. Estimation of Liability Measure

Full details of our estimation procedure are given in the Appendix. We give a brief overview here. We assume that the distribution of awards in Florida is stable over the relevant time period, implying that each year is drawn from the same underlying distribution. This allows us to reduce the noise from year-to-year variation in malpractice claims. The choice of 1980–86 is driven by two factors: (1) 1980 was the first year that specialty designations were included with each claim, and (2) Florida began instituting malpractice reforms in 1986, including a cap on malpractice awards in 1988.[12] Thus we take the distribution of

[12] In 1986, Florida abolished the collateral-sources rule, limited joint-and-several liability, and restricted contingent fees. In 1988, Florida imposed a cap of $350,000 on noneconomic damages (see Avraham 2006; Klick and Stratman 2007; Helland and Tabarrok 2003). From 1980 until 1985, Florida did have the English rule (the “loser pays” provision). See Hughes and Snyder (1995) for the details of this liability change. The effects of this rule are potentially significant; however, it is unclear why this would systematically bias the results. Although the English rule does appear to have moderately improved case quality, this would seem to affect all specialties equally and hence is captured in Florida’s overall liability risk. One concern is that Florida’s ranking of liability risk differs from other states in a systematic way. A comparison of Florida and the rest of the United States

claims in the intervening period to be representative of an unrestricted-claim environment.[13]

We first adjust for changes in the price level over time by converting all dollar amounts to 1980 dollars. Then we compute an average award by specialty, where the specialty designations are set by the Florida Department of Insurance (Table 1). To compute the estimated liability for specialty s in state i when there is no cap, we multiply the state-specific γ by the average award by specialty. For example, the estimated γ for Ohio is 1.12, and the estimated average annual liability of a general surgeon in Florida is \$4,961. Therefore, we estimate the liability of an Ohio general surgeon to be \$5,556. One potential issue is the small number of cases in certain specialties. For example, public health has only seven claims during the sample period. Clearly, such small samples make estimating the liability for these specialties quite noisy. Not surprisingly, specialties with small cell sizes in the Florida data are also those with small cell sizes in the PPCIS, and hence they are not driving the results.

To compute the effect of a cap, we truncate actual awards observed in Florida to the Consumer Price Index–adjusted award level in the particular state and then compute the sample mean implied by equation (6), adjusting for the state's γ. For example, Virginia instituted a \$1 million cap in 1983. We put this cap in 1980 dollars, multiply all observed Florida awards by Virginia's γ (.92), truncate observed awards that exceed the cap, and then compute the average award per doctor.[14]

One issue in computing relative liability exposure is how to calculate caps on noneconomic damages. States often cap only noneconomic damages. The Florida closed-claim data do contain information on noneconomic damages for some cases. One solution is to apply the relevant state cap to these damages. This is problematic because the breakdown is often not reported for settlements, which constitute 93 percent of closed claims not dropped by the plaintiff. Our solution is to take the average breakdown across all cases and reduce awards only in those cases in which the fraction of the award that is typically noneconomic damages exceeds the cap. During the period 1980–86, 58 percent of awards in Florida are for economic damages (lost wages, medical expenses, and the like), and 42 percent are for noneconomic damages.[15] We therefore apply this average rate to all awards in computing the effect of caps on noneconomic claims.

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confirms the conventional wisdom that Florida has a higher percentage of population that is Hispanic, foreign born, and over 65 but that it is otherwise quite similar to the rest of the country.

[13] The one exception, the National Practitioners Data Bank (NPDB), contains information on a few specialties, but researchers are instructed not to use this information because of reliability issues. The NPDB also covers only cases after 1990. Despite its problems, we use these data as a robustness check in Section 3.2.

[14] Our imputation methodology creates a link between realizations of Florida liability claims and the liability measures in all other states, whereas our theoretical treatment suggests a linkage only in the distribution of claims.

[15] This number is similar to the estimates of Tillinghast (2003), who finds that noneconomic damages constitute 52 percent of liability payments in 2003.

Table 1
Estimated Annual Liability

	Florida Data			
Specialty	Number of Claims Filed	Average Number of Physicians per Year	Average Annual Liability Award per Physician (1980$)	PPCIS, Number of Physicians
Allergy	13	92	332	35
Anesthesiology	737	913	6,807	514
Cardiovascular diseases	612	702	4,045	267
Dermatology	247	325	972	79
Emergency Room	1,077	587	6,564	221
Endocrinology	20	61	3,794	15
Gastroenterology	177	270	2,729	190
General practice	2,016	2,993	2,658	926
General surgery	1,748	1,505	4,961	586
Hematology	36	52	1,153	14
Internal medicine	1,833	2,086	3,016	706
Nephrology	48	128	1,154	34
Neurology	711	451	12,864	127
Obstetrics/gynecology	2,268	1,260	12,373	506
Oncology	6	138	20	53
Ophthalmology	571	725	1,620	298
Orthopedics	1,606	777	11,788	273
Otorhinolaryngology	380	322	5,088	151
Pathology	209	528	1,666	310
Pediatrics	775	1,143	5,062	366
Physical medicine	11	96	397	45
Plastic surgery	497	230	7,113	75
Psychiatry	131	1,018	174	467
Public health	7	42	136	1
Radiology	956	972	3,644	447
Rheumatology	13	93	129	24
Thoracic surgery	238	110	13,580	72
Urology	511	478	2,915	337

Note. The Florida data are closed-claim data for claims filed prior to 1987. The average number of physicians is from the American Medical Association Physician Master File, 1980–86. Awards include all claims adjudicated through 1998. The count of Physician Practice Costs and Income Survey (PPCIS) physicians is from regression column 2, Table 6. Florida data also include a category "undesignated," which is excluded from the analysis. Seven other Florida specialties either had no claim or no counterpart in the PPCIS and are thus excluded.

Table 2 provides an example of the importance of cross-state differences in determining which doctors have actually been exposed to a policy change. The table compares two states, Kansas and Nebraska. In 1988 Kansas imposed a $250,000 cap on noneconomic damages; in 1986 Nebraska imposed a $1,250,000 overall cap. By our estimate, Kansas's liability payments are 85 percent of Florida's, and Nebraska's are much lower at 46 percent.

As Table 2 shows, the Kansas cap affects specialties very differently depending on their underlying liability risk. Obstetricians and gynecologists find their liability risk reduced by 10 percent, while an allergist has no change in liability exposure. Contrast this with Nebraska. Given Nebraska's lower underlying lia-

Table 2

Examples of the Variation in the Effects of Capping Malpractice Awards

	Kansas			Nebraska			Average of States Imposing Some Cap between 1983 and 1988		
	Without Cap	With Cap	% Change	Without Cap	With Cap	% Change	Without Cap	With Cap	% Change
Allergy	281	281	.0	154	154	.0	377	377	.0
Anesthesiology	5,759	4,998	−13.2	3,153	3,153	.0	7,714	6,970	−9.6
Cardiovascular diseases	3,422	3,175	−7.2	1,874	1,874	.0	4,584	4,358	−4.9
Dermatology	822	822	.0	450	450	.0	1,101	1,101	.0
Emergency room	5,554	5,234	−5.8	3,041	3,041	.0	7,439	7,163	−3.7
Endocrinology	3,210	3,210	.0	1,757	1,757	.0	4,300	4,297	−.1
Gastroenterology	2,309	1,995	−13.6	1,264	1,264	.0	3,093	2,765	−10.6
General practice	2,249	2,106	−6.4	1,231	1,231	.0	3,012	2,874	−4.6
General surgery	4,197	3,988	−5.0	2,298	2,298	.0	5,622	5,426	−3.5
Hematology	976	976	.0	534	534	.0	1,307	1,307	.0
Internal medicine	2,552	2,409	−5.6	1,397	1,397	.0	3,418	3,291	−3.7
Nephrology	977	977	.0	535	535	.0	1,308	1,308	.0
Neurology	10,884	9,775	−10.2	5,958	5,958	.0	14,579	13,524	−7.2
Obstetrics and gynecology	10,468	9,420	−10.0	5,731	5,731	.0	14,022	13,022	−7.1
Oncology	17	17	.0	9	9	.0	22	22	.0
Ophthalmology	1,371	1,368	−.2	750	750	.0	1,836	1,834	−.1
Orthopedics	9,973	9,337	−6.4	5,460	5,460	.0	13,359	12,799	−4.2
Otorhinolaryngology	4,305	4,165	−3.3	2,357	2,357	.0	5,766	5,650	−2.0
Pathology	1,410	1,320	−6.4	772	772	.0	1,888	1,815	−3.9
Pediatrics	4,283	3,698	−13.7	2,345	2,345	.0	5,737	5,153	−10.2
Physical medicine	336	336	.0	184	184	.0	450	450	.0
Plastic surgery	6,018	5,677	−5.7	3,295	3,295	.0	8,061	7,730	−4.1
Psychiatry	148	146	−1.4	81	81	.0	198	197	−.5
Public health	115	115	.0	63	63	.0	154	154	.0
Radiology	3,083	2,853	−7.5	1,688	1,688	.0	4,130	3,927	−4.9
Rheumatology	109	109	.0	60	60	.0	146	146	.0
Thoracic surgery	11,490	10,777	−6.2	6,290	6,290	.0	15,390	14,820	−3.7
Urology	2,467	2,256	−8.6	1,350	1,350	.0	3,304	3,096	−6.3

bility risk, our estimate is that no change in liability risk occurred for any specialty as a result of the cap.[16] In effect, no policy experiment occurred in Nebraska, despite the change in law. Although Nebraska is an extreme example, there is considerable variation in the size of the changes faced by doctors. The last three columns of the table show our estimate of the average changes in liability due to caps during this period.

3. Estimation Results

Our estimation strategy is to treat the PPCIS as a stacked cross section for 1983 and 1988. Thus, observation i is a physician, k is physician specialty, s is state, and t is year. The basic regression model is

$$\ln(y_i) = \beta_0 + \gamma \ln(\text{liability}_{s,k,t}) + \lambda_t + \boldsymbol{\alpha}_{i,k,s,t} + \boldsymbol{\delta}_{i,k,s,t} + \beta \boldsymbol{x}_{i,k,s,t} + \nu_i, \quad (8)$$

where y_i is hours worked per week, $\text{liability}_{s,k,t}$ is computed using the sample analog to equation (4), λ_t is a dummy for 1988, $\boldsymbol{\alpha}_k$ is a set of dummies for physician specialty, $\boldsymbol{\delta}_s$ is a set of state dummies, and $\boldsymbol{x}_{i,k,s,t}$ are the control variables, including a set of county-level variables to account for local labor market conditions. We cluster the standard errors on the state. Descriptive statistics are given in Table 3.

3.1. Impact of Changes in Liability on Hours Worked

The first empirical results are outlined in Table 4. The coefficient of interest is the liability measure, which is estimated to be −.285, and it is statistically significant with a (asymptotic) *t*-statistic of −2.82. This estimate implies a relatively high sensitivity of labor hours to liability.

The specification in column 2 tests whether sole proprietors might be more sensitive to liability concerns because of potentially less risk sharing than can occur in large, multiphysician practices, and they also might have greater flexibility in choosing their working hours. Indeed, the estimated coefficient is substantially larger in absolute value at −.660, and it is also statistically significant.

Column 3 modifies the regression in column 1 to add in an interaction term with liability and age. The motivation is as follows: anecdotal evidence suggests that a high expected liability will often induce exit from high-risk specialties. While our data do not allow us to measure entry or exit decisions directly, they allow us to test for a closely related effect. Rather than a dichotomous choice to simply work or not work in response to a change in liability risk, it is possible that liability risk accelerates the standard retirement pattern of working fewer hours near the end of the life cycle: if physicians face higher risk, they will exit the profession gradually rather than simply stop working abruptly.

[16] While it may seem odd that Nebraska passed a damage cap that did not alter physician liability, this does seem to be the case. In the NPDB, there are 25 medical malpractice trials in Nebraska. The average award was $245,410, with two awards, both in 1995, above the million-dollar cap that were subsequently reduced.

Table 3
Descriptive Statistics for the Full Sample ($N = 7{,}247$)

	Mean	SD
Weekly hours	58	15
Annual income	126,085	101,545
Medical malpractice premium	12,157	13,072
Liability measure	7,639	8,146
Age	47.0	10.3
Male	.92	.27
Solo practice	.34	.47
Board certified	.73	.45
Foreign medical school	.23	.42
Hispanic	.03	.16
Asian	.11	.32
Black	.02	.15
County-level controls:		
Physicians per 1,000	2.0	1.2
Hospitals per 1,000	.03	.02
Hospital beds per 1,000	6.2	3.7
% Population in health maintenance organization	8.8	7.5
% Population ages 0–14	21.7	2.9
% Population ages 65 and over	11.5	3.4
% Population black	11.7	12.3
% Urban	78.4	24.3
% Population below the poverty line	12.0	5.1
Median income (1980$)	20,498	3,816

Note. For variables with missing values, statistics are computed on the available data.

To test this, we interact the liability measure with a counter variable that takes a value of 0 for ages less than 55, 1 at age 55, 2 at age 56, 3 at age 57, and so on.[17] The results are given in column 3. The coefficient on liability, −.278, is similar to that in the initial regression (column 1), and it also remains statistically significant. The estimated coefficient for the interaction term is −.00176 and is highly statistically significant, with a *t*-statistic of −3.20. The magnitude is relatively small, however. The estimated elasticity for a 65-year-old physician is −.297, or .019 points lower than for a physician who is 55 or younger. Although small, these results imply that liability has an increasing effect as physicians get older, which is consistent with the anecdotal evidence of early retirement behavior in high-risk specialties.

To examine this age effect more directly, we restrict the sample to physicians who are 55 or older and reestimate the regression. The results are reported in column 4. In this specification, the liability measure is very large relative to previous estimates, −1.224, with a *t*-statistic of −4.19. This estimate implies that a 10 percent increase in malpractice liability risk is associated with a 12 percent decrease in hours worked. This result is consistent with the specification using

[17] We experiment with other specifications, using younger and older ages. There is not much of an effect below 55, and specifications starting after 55 tend to show larger coefficients on the interaction.

Table 4

Regression Results of Physician Behavioral Variables on the Liability Measure

	ln(Weekly Hours) (1)	ln(Weekly Hours), Sole Proprietors Only (2)	ln(Weekly Hours) (3)	ln(Weekly Hours), Age 55 or Older (4)
ln(Liability)	−.285**	−.660**	−.278**	−1.224**
	(.101)	(.210)	(.100)	(.292)
ln(Liability) × (Age − 54)			−.00176**	
			(.00055)	
N	7,104	2,404	7,104	1,749
R^2	.15	.18	.16	.16
F-test			12.28	
Prob > F			.00	

Note. Clustered standard errors (by state) are in parentheses. All regressions contain the following control variables: age of physician; age squared; binary variables for gender, board certification, and graduation from a foreign medical school; race (Asian, Black, Hispanic); a constant; dummy variables for year, state, and physician specialty; and county-level controls for doctors per 1,000 residents, hospitals per 1,000 residents, hospital beds per 1,000 residents, percentage of the population enrolled in a health maintenance organization, median income, percentage urban, percentage black, percentage below the poverty line, percentage ages 0–14, and percentage ages 65 and older. All but regression 2 contain a binary variable for solo practice. The F-test in column 3 tests joint significance of liability and the interaction term. The interaction term, ln(Liability) × (Age − 54), takes a value of zero for physicians under age 55.

** Significant at the 1% level.

the full sample, which implies that older physicians respond strongly to liability risk.[18]

3.2. Alternative Specifications and Robustness Checks

In Table 5 we estimate a set of regressions using alternative specifications to check the implications and robustness of our results. In column 1, we add a set of dummy variables for other state laws affecting medical malpractice liability. It is often the case that when states reform their legal system, they do so with a host of other changes in addition to caps on damages, and it is possible that our liability measure is picking up the marginal effects of these other changes (Avraham 2006). The liability measure is actually larger and more statistically significant than in the baseline regression from Table 4.

In column 2, we utilize an alternative control for the liability situation in the state. We construct a measure of "other" liability that is the average liability for all specialties other than the physician's for a given state and year. The estimated effect of the physician's own liability is very similar to our baseline estimate, which suggests that we are not simply measuring the overall liability situation in the state.

In columns 3–5, we estimate the sensitivity of the results to other potential issues in the data. Column 3 reports the results of an instrumental variables regression accounting for the relatively large change in tax rates induced by the federal Tax Reform Act of 1986 (Pub. L. No. 99-514, 100 Stat. 2085). Our concern is that the change in labor hours reflects changes in marginal tax rates rather than the changes in liability risk.[19] We find that the coefficient is even larger than when taxes are not accounted for.

In column 4, we estimate the sensitivity of our results to our particular draw of cases from the Florida sample. Specifically, we bootstrap the sample of Florida claims for 1,000 replications, recreating the liability measures and rerunning the regressions. These results suggest that our findings do not hinge on the particular draw from the Florida file.

Finally, we report the results using log(Income) as the dependent variable. Income offers a potentially interesting check on our labor hour regressions because if physicians are cutting back on hours, it would probably show up in lower income as well.[20] The liability effect is again negative and significant, consistent with what we find in the labor hours regressions.

[18] These estimates may understate the full effect of liability on labor supply. First, it is possible that physicians select a specialty in part on the basis of their labor supply elasticity. Second, we have excluded part-time physicians, including physicians in partial retirement, who may be more sensitive to liability concerns.

[19] Showalter and Thurston (1997), using the 1983 cross section of the PPCIS, find that marginal tax rates have a significant effect on physician labor supply for some segments of the physician population (for example, sole proprietors).

[20] Income is reported as a gross measure, but it has several problems. For one, it is measured in categories, and so actual income is not observed. We also do not observe the details of contracts with hospitals or physician working groups to account for who is paying the malpractice premium.

Table 5
Alternative Specifications, by Dependent Variable

	ln(Weekly Hours)				ln(Income)
	(1)	(2)	(3)	(4)	(5)
ln(Liability)	−.399**	−.294**	−.441**	−.183*	−.597*
	(.130)	(.107)	(.128)	[−.400,−.015]	(.256)
N	7,104	7,104	5,987	7,415	6,240
R^2	.16	.15	.14		.30

Note. Clustered standard errors (by state) are in parentheses. All regressions contain the following control variables: a constant; dummy variables for year, state, and physician specialty; and county-level controls for doctors per 1,000 residents, hospitals per 1,000 residents, hospital beds per 1,000 residents, percentage of the population enrolled in a health maintenance organization, median income, percentage urban, percentage black, percentage below the poverty line, percentage ages 0–14, percentage ages 65 and older, age, age squared, male, racial categories (Asian, black, and Hispanic), and binary variables for solo practice, board certification, and graduation from a foreign medical school. Column 1 includes dummy variables for a cap on noneconomic awards, a cap on total awards, abolishment of joint-and-several liability, abolishment of collateral-sources rule, contingent fee restriction, periodic payment rule, and victims' fund. Column 2 includes ln(Average Liability of Other Specialties). Column 3 includes ln(1 − Marginal Tax Rate) as an explanatory variable. It is instrumented with ln(1 − MSTR), where MSTR is the highest marginal state tax rate in the state of residence. Column 4 gives the average parameter estimate for 1,000 bootstrap replications of the Florida distribution of claims. Square brackets indicate the 95 percent confidence interval for the estimated parameters, with 5 percent in each tail. The resampling resulted in slightly different sample sizes across replications: N is the average.
* Significant at the 5% level.
** Significant at the 1% level.

3.3. Tests Using the National Practitioners Data Bank

We next evaluate the sensitivity of our results to using the Florida claims data as a base. The National Practitioners Database (NPDB) is published by the Department of Health and Human Services (HHS) pursuant to the Health Care Quality Improvement Act of 1996 (42 U.S.C. 11101). The act requires insurers to report all medical malpractice payments made on behalf of individual practitioners to HHS. The NPDB contains information on over 200,000 medical malpractice payments made on behalf of practitioners in all 50 states from September 1, 1990, to December 2006. These data do not extend back to the 1980s, but they do include claim data by state and a few identifiable specialties beginning in the early 1990s. We are able to identify two specialties, surgery and obstetrics, that match the categories we used with the Florida data. To be comparable with the Florida data, we need a reasonable number of claims for each specialty, and we need states with no caps on total damages or noneconomic damages. New York and Texas for the years 1991–95 meet these criteria: New York had 2,161 surgery claims and 644 obstetrics claims; Texas had 1,124 surgery claims and 360 obstetrics claims. We use the data from these two states for these two specialties and compare the results to those from the Florida data.

The results are given in Table 6. The coefficients on liability are larger but now statistically insignificant, with the exception of the interaction term. These

Table 6

Regression Results Using Alternative Data

	ln(Annual Hours) (1)	ln(Weekly Hours) (2)	ln(Weekly Hours), Sole Proprietors Only (3)	ln(Weekly Hours) (4)	ln(Weekly Hours), Age 55 or Older (5)
Florida data, surgery and obstetrics/gynecology only:					
ln(Liability)	−.577	−.733	−1.085	−.738	−1.608
	(−.464)	(−.479)	(−1.099)	(−.489)	(−1.67)
ln(Liability) × (Age − 54)				−.00681*	
				(−.00297)	
N	1,064	1,086	391	1,086	313
R^2	.14	.16	.21	.16	.28
NPDB data, New York base:					
ln(Liability)	−1.764	−2.115	−2.619	−2.122	−6.349*
	(−1.303)	(−1.288)	(−2.689)	(−1.292)	(−3.048)
ln(Liability) × (Age − 54)				−.00739*	
				(−.00277)	
N	1,064	1,086	391	1,086	313
R^2	.14	.16	.21	.16	.29
NPDB data, Texas base:					
ln(Liability)	−.63	−.8	−1.105	−.792	−2.28
	(−.492)	(−.487)	(−1.083)	(−.488)	(−1.419)
ln(Liability) × (Age − 54)				−.00657*	
				(−.00283)	
N	1,064	1,086	391	1,086	313
R^2	.14	.16	.21	.16	.28

Note. Clustered standard errors (by state) are in parentheses. All regressions contain the following control variables: a constant; dummy variables for year, state, and physician specialty; and county-level controls for doctors per 1,000 residents, hospitals per 1,000 residents, hospital beds per 1,000 residents, percentage of the population enrolled in a health maintenance organization, median income, percentage urban, percentage black, percentage below the poverty line, percentage ages 0–14, and percentage ages 65 and older. NPDB = National Practitioners Database.

* Significant at the 5% level.

results are not too unexpected: the smaller sample size diminishes the statistical power of the regressions.

The table also presents results for the New York data from the NPDB. In this case, all the coefficients are negative, but most are statistically insignificant. Finally, results for the Texas data are shown, and again all the coefficients are negative but statistically insignificant, with the exception of the interaction term. We conclude that the NPDB data qualitatively support our broader results using the Florida data.

3.4. Comparison of Aggregated Index to National Association of Insurance Commissioners State Averages

Our next robustness test compares our constructed index with aggregate data from the NAIC. Our index computes a predicted liability for each specialty and state. For those states that imposed a cap between 1983 and 1988, the predicted liability measure should change. If we aggregate our index to the state and year level, weighting by the number of physicians in each specialty, we should approximate the average claim per doctor in the NAIC data.

First, we compute an average claim per doctor for the years 1980–89, measured in 1980 dollars, using the NAIC data. Then we split the sample and compute an average claim per doctor for each state for the periods 1980–85 and 1986–89, which roughly matches the two time periods we used to construct our index. This gives us 102 observations. Then we aggregate our index number, weighting by the number of physicians in each specialty and state for the same time periods. We then run a regression of the NAIC averages on our aggregated index values. The first regression results in

$$\underset{}{\text{NAIC}} = \underset{(238.02)}{551.85} + \underset{(.027)}{.57}\text{Index}$$

(N = 102, R^2 = .81), with standard errors in parentheses. We also include a dummy variable for being in the second time period (1988):

$$\text{NAIC} = \underset{(235.08)}{-171.26} + \underset{(.024)}{.57}\text{Index} + \underset{(205.85)}{1{,}265.22}\ (1988)$$

(N = 102, R^2 = .86). In both cases, the aggregated index is highly correlated with the aggregate award per doctor. We view this as supportive evidence that our index is a reasonable measure of the changes occurring across the various states.

3.5. Liability Measure and Malpractice Premiums

We next test the link between our liability measure and self-reported malpractice premiums. Our liability measure is admittedly imperfect, but if it is capturing anything of interest, it ought to be correlated with observed malpractice premiums. The PPCIS asks physicians for the dollar amount of their malpractice premiums. This measure is also quite noisy: a given physician's malpractice premium can be complicated by joint arrangements in multiphysician practices and by arrangements through other parties such as hospitals. In Table 7, we report the results of regressing the self-reported measure of malpractice premiums on our liability measure. Column 1 uses only a constant and the liability measure. Our liability measure is highly correlated with observed premiums and alone can explain 18 percent of the variance. Given the measurement problems with both variables, this result is surprisingly strong. It is also heartening that the number implies that a $1 increase in liability is associated with a nearly equal increase in the observed malpractice premium.

Column 2 adds in some physician-specific control variables and the county-level variables. Column 3 adds state, specialty, and year controls. These additional variables decrease the estimated coefficient substantially, but they are still highly statistically significant. Taken together, these results indicate a strong, positive relationship between actual liability and observed malpractice premiums, although we are hesitant to place a great deal of faith in the exact coefficient estimates because we know little about the underlying insurance contracts.

Because of the ambiguity over how malpractice premiums are set (Baicker and Chandra 2006), we reestimate using only claims adjudicated through 1986 rather than those adjudicated up through the end of the 1990s. This might be a better approximation of the information that insurers used in setting malpractice premiums during this period. The results are similar to those found previously, although the coefficient estimates are closer to 1, suggesting a dollar-for-dollar link between expected liability and malpractice premiums.

4. Conclusion

In this paper, we estimate the impact of medical malpractice liability on physician labor supply. We use two unique data sources: (1) We develop a new measure of liability risk based on actual liability award data in Florida, combined with aggregate award data from other states. Our measure of liability risk is a continuous variable and varies by specialty, state, and the details of existing medical malpractice award caps. It contrasts with the more typical approach of using binary variables to indicate the existence of a cap. (2) We use individual-level data from two nationally representative cross sections of physicians: the PPCIS from 1984 and 1988. These two surveys contain detailed information on physicians and practice behavior. In addition, these surveys bracket a period of significant state-level activity in instituting liability caps, providing the primary econometric identification for our liability measure.

We find that increases in liability decrease the number of hours a physician

Table 7

Regression of Self-Reported Medical Malpractice Premium on Liability Measure

	All Claims			Only Claims Adjudicated by 1986		
	(1)	(2)	(3)	(4)	(5)	(6)
Liability	.699**	.684**	.225**	1.053**	1.042**	.350**
	(.105)	(.100)	(.061)	(.159)	(.153)	(.087)
Age		702.2**	437.2**		711.4**	435.1**
		(138.6)	(119.8)		(137.6)	(120.9)
Age squared		−6.9**	−4.4**		−6.9**	−4.3**
		(1.4)	(1.3)		(1.4)	(1.3)
Male		1,127.6⁺	−136.9		1,365.8*	−122.8
		(622.6)	(609.7)		(632.4)	(611.9)
Solo practice		−1,049.0**	−711.6**		−931.0**	−700.4**
		(242.9)	(198.1)		(246.7)	(200.7)
Board certified		1,536.6**	1,113.1**		1,613.2**	1,113.9**
		(244.1)	(281.1)		(242.0)	(281.5)
Foreign medical school graduate		563.0	656.6		599.0	656.8
		(541.7)	(454.4)		(535.3)	(455.7)
Race of physician:						
Asian		−1,177.9⁺	−1,114.8*		−1,186.3⁺	−1,108.4*
		(671.6)	(473.9)		(663.1)	(475.0)
Black		−42.1	−967.0		44.5	−998.6
		(956.0)	(814.0)		(999.7)	(817.7)
Hispanic		509.2	−730.5		431.9	−752.5
		(571.1)	(609.5)		(568.0)	(606.0)
County-level demographic controls	No	Yes	Yes	No	Yes	Yes
State, year, and specialty controls	No	Year only	Yes	No	Year only	Yes
N	6,346	6,310	6,310	6,346	6,310	6,310
R^2	.18	.33	.49	.17	.31	.49

Note. Clustered standard errors (by state) are in parentheses. All regressions contain a constant. County-level controls are controls for doctors per 1,000 residents, hospitals per 1,000 residents, hospital beds per 1,000 residents, percentage of the population enrolled in a health maintenance organization, median income, percentage urban, percentage black, percentage below the poverty line, percentage ages 0–14, and percentage ages 65 and older.

⁺ Significant at the 10% level.

* Significant at the 5% level.

** Significant at the 1% level.

works. The effect is strongest for physicians who are 55 or older, and the effect increases modestly with age. The fact that the impact on hours worked is largest among physicians over 55 is consistent with previous research, which finds the largest impact of liability on retirements (Kessler, Sage, and Becker 2005). Sole proprietors also exhibit a relatively strong reaction to variation in liability risk.

This observed sensitivity of hours worked to liability risk is potentially important in the context of the current political debate over whether to have a nationwide cap on malpractice awards. There are many anecdotes and some firm empirical work concerning the impact of liability risk on physicians' exit from high-risk specialties such as obstetrics and surgery. Our results show that there are also labor effects on the intensive margin—physician behavior other than the participation decision—thereby suggesting a larger effect of medical malpractice liability than previously thought. In particular, access to health care can be affected not only by physician exit but also by physicians cutting back on their hours worked. We can make a very rough approximation to gauge the magnitude of the effect: There were an estimated 763,200 active physicians in the year 2005 (U.S. Health and Human Services 2006). Our baseline estimate of an elasticity of $-.285$ for all full-time physicians implies that a 10 percent increase in expected liability would lead to a 2.85 percent decline in the average physician's work hours. This is roughly equivalent to one in 35 physicians leaving the workforce entirely, or about 21,800 physicians.

We also find that our liability measure is highly correlated with a self-reported measure of malpractice premiums. Although this result is expected by economists, previous empirical work is ambiguous on the link between liability claims and malpractice premiums. As discussed by Baicker and Chandra (2006), malpractice premiums are influenced by several mechanisms, including multiple years' worth of liability exposure, investment returns, and the competitive climate.

Finally, comparing the effect of a given dollar-level cap in malpractice awards across states suggests that the impact of a cap varies widely depending on two factors: the legal environment in a given state, particularly its propensity to generate large malpractice awards, and the health care environment and its general level of cost. This observed variation seems to suggest that having a uniform nationwide standard on malpractice awards might not be optimal. But this point is worthy of additional research that accounts for the various tradeoffs involved.

Appendix

A1. Factors of Proportionality

Estimated factors of proportionality (γ^S) are computed as follows:

1. The NAIC collects firm-level data on medical malpractice claims by state and year. We aggregated these data to estimate the total claims incurred for each

state and year from 1980 to 1986. The resulting variable we refer to as NAIC (year, state).

2. Using doctor counts by specialty from the AMA Physician Master File, we constructed a count of the number of doctors for each year, 1980–86, in each of the 36 specialties coded in the Florida claims data. The 1984 data are missing, so we averaged the 1983 and 1985 values to impute the 1984 counts. The resulting variable we refer to as DOCCOUNT (specialty, year, state).

3. Using the Florida closed-claim file, we computed a total dollar value of claims filed in each year for each specialty. We then divided these numbers by the number of Florida doctors in that specialty for that year using the results from step 2. This gives an average claim per doctor, by specialty and year, which we refer to as AVGCLAIM (specialty, year, Florida).

4. Following equation (5), we then computed an estimate of the total claims filed in each state-year combination by multiplying AVGCLAIM × DOCCOUNT and summing over specialty. We refer to the resulting variable as TOTCLAIM (year, state).

5. We then compute a raw factor of proportionality, γ, by dividing NAIC (year, state) by TOTCLAIM (year, state). Then the average value for the 7 years is computed for each state, except for states that imposed a cap on liability awards between 1983 and 1988. For those states, we average only over the noncapped years. We then normalize the γ^S value by the value for Florida and use the result to adjust claims to compute the liability measure as outlined.

A2. Estimating the Liability Measure for Each State, Year, and Specialty

The liability measure is computed using the following algorithm:

1. For state *i*, in year *t*, specialty *s*, all awards (*i*, *t*, *s*) from the Florida data are adjusted to be in 1980 dollars.

2. For states with no caps, the liability index is computed as AVGCLAIM (specialty, year, Florida) multiplied by the estimated *g* in the state. Therefore, states with no caps between 1983 and 1988 have the same value for the liability index for both years.

3. For states with a cap, each award from the Florida data is first multiplied by the state's estimated *g* and is then segmented into an economic (ECON) and noneconomic (NECON) component, the ECON = .58 (award) and NECON = .42 (award). Then the particulars of the state's rules are applied to ECON and NECON.

For example, suppose there is a $1,000,000 award (1980$) for thoracic surgery in the Florida data. We want to adjust this to compute an index value for thoracic surgeons in New Hampshire, which instituted a $250,000 cap on noneconomic damages in 1986. First, we adjust the award by New Hampshire's estimated *g*, .84, to obtain a value of $840,000. Then this value is split into an economic and noneconomic component, $487,200 and $352,800, respectively. We compute an adjusted award under conditions of the cap: 487,200 + 187,956 = 675,156, where the 187,956 is the $250,000 cap in 1980 dollars. So the cap has reduced the award from $840,000 to $675,156. Every award against a thoracic surgeon in the Florida data is similarly adjusted, and a mean value of the adjusted awards is then computed to construct the index value.

For clarity, we present the steps of creating the index value for general surgery in Kansas in Table 2. The work is shown in Table A1.

1. We start with the set of all medical malpractice claims against general surgeons in Florida, with their associated award amounts (in dollars), during the period 1980–86. Awards are adjusted to be in 1980 dollars. For example, 10 claims for general surgery are listed in column 1 in Table A1.

2. The next step is to rescale the empirical distribution of claims to reflect differences in average observed claims in Kansas. Each claim is scaled by a cost adjustment that compares average claims in Florida with average claims in Kansas (see Section A1 for details on how the scaling factor is computed). The adjustment factor is approximately .846; each claim is multiplied by this factor, which results in the values in column 2.

Summing column 2 and dividing by the total number of physician-years gives an estimate of annual liability costs for Kansas general surgeons without a liability cap: $4,197 (see Table 2). The comparable number for Florida general surgeons is $4,961. Obviously, the Kansas liability cost is a simple scaling of the Florida cost, but this represents only a segment of the liability measure.

3. Next we split each Kansas claim into two components: one part representing economic damages (58 percent) and the other part representing noneconomic damages (42 percent). These values are in Table A1, columns 3 and 4.

4. Then we apply the particular rules in Kansas to the distribution of claims. Kansas imposed a $250,000 cap on noneconomic damages in 1988. Adjusting to 1980 dollars, this is a cap of $174,134. Any claim with noneconomic damages above this limit is given the value of the cap—there are 15 such cases, out of 583 nonzero claims. The adjusted values of the claims are in columns 5 and 6, and the sum of the economic and adjusted noneconomic damages is in column 7, which represents the total claim when the cap is in force. Claims for which the noneconomic component does not exceed the cap are not changed. This creates a nonlinearity in the effect of the scaling.

Finally, the adjusted values in column 7 are averaged to compute an estimate of annual liability costs when a cap is in place. The value for Kansas general surgeons is $3,988 (see Table 2). All Kansas general surgeons in 1988 have this value for their liability measure. All Kansas general surgeons in 1983 have the upcapped value of $4,197.

We repeat this process for each specialty, in each state, for each sample year (1983 and 1988). There is a different distribution of claims for each specialty in Florida that acts as the primary distribution for each specialty, to be scaled by state-level costs (γ^S).

Table A1

Derivation of Liability Measure for General Surgeons

			Value without Cap		Value with Cap		
	Claims in Florida (1)	Adjusted Claims: Kansas (2)	Economic Damages (3)	Noneconomic Damages (4)	Economic Damages (5)	Noneconomic Damages (6)	Total Value of Claim with Cap (7)
1	2,232,116	1,888,503	1,095,332	793,171	1,095,332	174,134	1,269,466
2	1,295,806	1,096,329	635,871	460,458	635,871	174,134	810,005
3	1,100,633	931,201	540,096	391,104	540,096	174,134	714,230
4	1,088,705	921,109	534,243	386,866	534,243	174,134	708,377
5	1,052,555	890,524	516,504	374,020	516,504	174,134	690,638
6	1,033,829	874,681	507,315	367,366	507,315	174,134	681,449
7	972,088	822,445	477,018	345,427	477,018	174,134	651,152
8	696,534	589,309	341,799	247,510	341,799	174,134	515,933
9	644,684	545,441	316,356	229,085	316,356	174,134	490,490
10	627,749	531,113	308,045	223,067	308,045	174,134	482,179
Annual physician liability	4,961	4,197					3,988

Note. Values are in 1980 dollars. Column 1: claims from Florida data for general surgeons, 1980–86. Column 2: column 1 × Kansas adjustment (.846). Column 3: .58 × column 2. Column 4: .42 × column 2. Column 5: column 3. Column 6: min(column 4, 174,134). Column 7: column 5 + column 6. $N = 1{,}748$ claims against general surgeons in Florida. For annual physician liability, average across all claims for which the denominator is the number of general surgeon physician-years in Florida, that is, 10,536.

A3. Monte Carlo Experiment to Understand Properties of Data Inference

A3.1. Background Issues

Our proxy for expected liability costs is unusual because of its combination of actual claims and state-level averages. Because of its complexity, we are unable to derive the asymptotic properties of ordinary least squares (OLS). However, we have worked through some Monte Carlo simulations, which we report in this section.

The setup of the simulation is to compare the OLS results from two models: one in which expected liability is measured without error (the true model) and the other in which the expected liability must be inferred from the distribution of claims from one state, scaled by averages in other states (the strategy we use in this paper).

In brief, we generate hypothetical medical malpractice claims: a set of claims for each state-specialty combination, each from a different lognormal distribution (for example, there is a set of claims for Florida general practitioners, another set of claims for California general practitioners, and so on). Distributions are proportional to one another across states, following the assumption given in equation (5), and are scaled to match the mean values we observe in the NAIC data. We assign 10 states to have a cap on awards. With this information, we compute an average liability for each state; for those states with a cap, we can compute it with and without the cap. This process gives the true expected liability measure.

We then compute an alternative estimator based on the claims from one state and the state-level means for other states. This follows our data construction methods outlined in Section 3.4. Next, we generate a set of dependent variables using

$$y_{it} = \beta_0 + \beta_1(\text{liability})_{it} + u_{it},$$

where $\beta_0 = 1.0$ and $\beta_1 = .5$, liability is the true liability measure, and u_{it} is an independent and identically distributed normal random variable. The terms β_0 and β_1 are estimated twice, once with the true liability measure and once with the proxy. We repeat the exercise 1,000 times.

The results of the simulation are given in Table A2 and Figure A1. From Figure A1, for the slope parameter β_1, we see that using the true liability measure gives the standard asymptotic normal pattern centered on the actual value of .5. The distribution using the proxy is roughly symmetric, but it is biased, with a mean of .41. It also has a much higher standard deviation: .125 compared with .019. Both of these results are understandable: the bias results from measurement error, leading toward an underestimate of the true parameter. The higher dispersion comes from the heavy reliance on claims from one state. This latter point implies that we have fewer degrees of freedom than would be the case had we the true liability measure.

It seems reasonable that these results would apply to our basic regression

Table A2
Summary Statistics for the Monte Carlo Experiment

	Mean	SD	Min	Max
Using true liability measure:				
β_0	1.003	.115	−.262	2.283
β_1	.499	.019	.420	.559
Using estimated liability measure:				
β_0	1.235	.322	−.911	2.877
β_1	.410	.125	.016	1.002

results. Although biased toward zero because of measurement error, we should be aware of the potential countervailing problem that the estimators have more dispersion than would be typical with OLS. We do not know how to compute the right number of degrees of freedom, but we can evaluate the sensitivity of our results to this problem.

From Table 4, we have four significant results for the liability coefficient. In columns 1, 2, and 4, the associated *t*-statistics of 2.82, 3.14, and 4.19, respectively, would all be significant at the 5 percent level with only 4 degrees of freedom. Column 4 has a joint test, with an *F*-statistic of 12.28; this would be significant at the 5 percent level with 6 degrees of freedom (denominator). Given the amount of information used in the estimates—several thousand claim files that are aggregated in different ways across 50 states (and the District of Columbia) and 28 specialties using state-specific means from an alternate data source—it seems unlikely that accurately accounting for the degrees of freedom would overturn our results. A more difficult problem is assessing the bias in the standard error when using the estimated liability measure.

A3.2. Details of the Monte Carlo Experiment

The objective of the Monte Carlo simulation is to experiment with how the estimates are affected by using a single state's claims, combined with state averages in other states. We simplify the analysis to focus on this issue.

The Monte Carlo simulation was conducted as follows:

1. Using the full closed-claim Florida data set (1980–86), all claims that had zero payouts were dropped. Claims were adjusted to 1980 dollars. Specialties that had fewer than 100 remaining claims were also dropped. The remaining specialties were anesthesiology, cardiovascular diseases, emergency room, general practice, general surgery, internal medicine, neurology and surgery, not specified, obstetrics and gynecology, orthopedics, osteopathy, otorhinolaryngology, pediatrics, plastic surgery, and radiology.

2. A set of claims for each state was created by multiplying the Florida claims in step 1 by the state-specific adjustment factor.

3. Using the data generated in step 2, we estimated a log-normal distribution for each state-specialty combination.

4. Using the parameters from step 3, we generated a set of claims for each

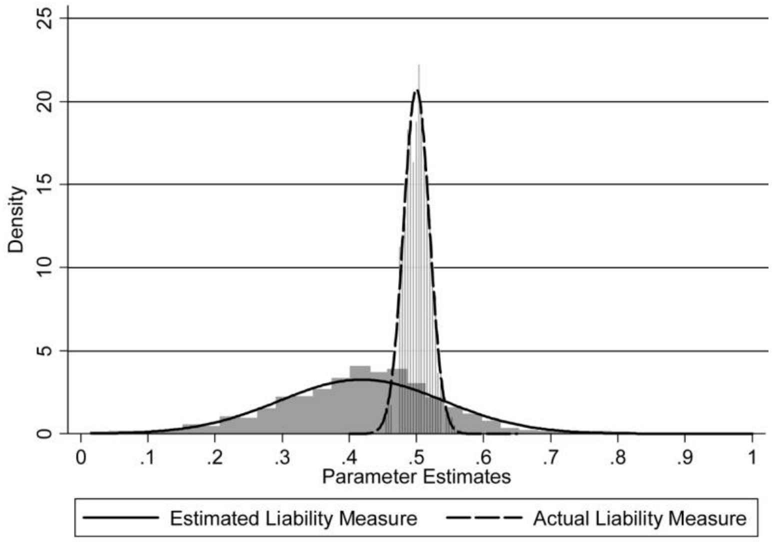

Figure A1. Histograms of estimates of slope parameters from the Monte Carlo experiment

state-specialty combination. The number of generated claims matched the number of claims in the original Florida sample, less the zero observations.

5a. We then created a true liability index from the claims in step 4: claims were averaged by state-specialty combination. This created a true liability index for each state-specialty combination.

5b. Ten states were randomly chosen to have truncated values: awards exceeding \$250,000 were given a value of \$250,000. The liability measure was recalculated for these 10 states. The states are Mississippi, Kansas, New Hampshire, Delaware, Ohio, Wyoming, Kentucky, Vermont, Indiana, and Idaho.

6. We created a new set of observations in which the number of specialists in each state roughly matches the number found in the PPCIS data. The liability values from step 5a were matched with the values from step 5b by specialty and state. Then the capped values were matched for the second year, by specialty and state.

7. A dependent variable was then created with the formula $y_{sct} = 1 + .5\ \text{liability}_{sct} + e_{sct}$, where s is state, c is specialty, and t is time (period 1 or period 2). The error term was generated as an independently and identically distributed normal variable with a variance twice that of the sample variance of the liability measure.

8. An estimated liability (estliability) measure was then generated on the basis of the procedure given in the main text: Florida claims were scaled by state averages to generate pseudodistributions for each state-specialty combination.

9. Two regressions were run (5,787 observations): (1) y_{sct} on (1, liability$_{sct}$) and (2) y_{sct} on (1, estliability). The parameters were saved as observations in the Monte Carlo simulation.

10. Steps 4–9 were repeated 1,000 times to generate the distributions given in Figure A1.

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