

Are Bad Physicians Pardoned with Shorter Litigations? Evidence From Med-Mals in FL¹

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Abstract: An important but under-researched issue of medical malpractice (med mal) litigations is how physicians' prior med-mal experiences affect their current behavior. Using Florida data on closed med-mal claims, this study shows that if physicians have prior paid claims, their current litigation is resolved faster and is associated with less cost. This pattern significantly exists after controlling for fixed characteristics of each physician, damage severity, insurers' dummies, among many other explanatory variables. Selection of patients towards physicians with more prior med-mals is evaluated using NPDB. A "learning" hypothesis is suggested to explain this stylized fact. As a theoretical motivation, a dynamic version of the divergent expectations (DE) bargaining model is developed. The model predicts, consistent with the data, that physicians have a more realistic analysis of med-mal litigation if they have prior experience. Many robustness checks are carried out to test the results. Knowing that Med-Mals litigations last too long and impose expensive legal procedures, introducing a new mechanism to cut them could save significant amounts of time and money for both the physicians and the tort system.

¹ An older version of this paper has been circulated with this title: *Learning How to Handle Malpractice Litigation from Experience: Evidence from Florida*

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1. INTRODUCTION

There is a significant amount of literature on different factors that may reduce litigation costs to the tort system, including length of litigations. Among different claims, medical malpractices (med-mals) are have a long duration⁴ (about four years in Florida) and many studies have tested how various factors affect their length. However, there is no study that investigates the impact of physicians' prior med-mals on the length of their current trials. This study adds to the literature by providing evidence of correlation between past experience and current behavior. A “learning” hypothesis is tested, both through a theoretical divergent expectation (DE) model, and empirical evidence from Florida medical malpractice dataset. Results suggest that med-mal cases of physicians who are familiar with litigation are end up faster and with less amount of litigation payment to defense counsel.

There are many reasons to believe that coping with the stress and complicated rules of litigation is not easy for physicians. Brenner (2010) describes litigation as a perplexing road that starts with being sued and ends with settlement, verdict, or possible appeal. The litigation process includes learning the options of insurance contract, choosing an attorney, preparing depositions, and coping with the lawsuit. Physicians who have never gone down this road may have a harder learning the signs and tricks to navigate the legal system. Physicians accumulate knowledge by going through med-mals, which facilitates their potential of early settlement in future cases.

The theoretical framework of this paper is based on the divergent expectation (DE) model, which is widely used in litigation literature. Priest and Klein (1984) first

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used the DE model to present a theoretical explanation for the positive trial rate despite the increased expenses associated with going to court. Waldfogel (1995, 1998) estimates the parameters of the DE model using federal civil case records to compare the outcome of this model with the outcome of asymmetric information litigation models⁵. I extend the DE model to a dynamic version in which a defendant with multiple litigations can update her beliefs about the court's decision standard, i.e., the norm to which each case is compared. Theoretical findings show that a defendant who has experienced more med-mals ends up having more realistic analyses of the litigation process and is more likely to settle in the early stages of litigation.

The Florida dataset of med-mals provides an opportunity to track physicians over multiple malpractices. In this study, the history of each defendant indicates the number of prior paid med-mals that she had; therefore, the *history* is calculated per physician-case and increases as the physicians goes through more and more litigation procedures. We also can measure total number of med-mals that each physician is being involved.

FL data supports a strong negative correlation between *history* (number of prior med-mals) and length of current litigation, which is consistent with the hypothesis of learning how to resolve cases more effectively. In addition, as empirical estimation suggests, priory litigated physicians pay less litigation cost in their current case, which is one more indication of avoiding of unnecessary expenses. Many robustness tests are carried out, including testing the results in a fixed effect (FE) framework, which captures physicians' fixed heterogeneities. The results are also robust to exclusion of rightly censored data in the recent years of the data, and exclusion of those physicians-cases with very high number of prior med-mals.

⁵ See Bebhuk (1984) and Spier (2004) for more literature review.

There is a concern whether the FL data which is restricted to physicians with paid claims encounters endogenous selection. Studdert, et. al. (2016) shows that physicians with prior med-mals are more likely to be litigated again. There are two explanations for this fact: First, physicians' skill (known as "type" in mechanism design literature) determine number of med-mals they would be involved. Second, it is easier for patients to defeat physicians with bad history (conditional on the fact that the history is publicly known).

We control for the time-invariant skills by using Fixed Effect (FE) specification. Addressing the second channel to endogeneity is a more complicated job. It's more than decades in FL that patients easily access to physicians history through the web, and it may incentivize them for filing the law suit even though the physician is not really liable or the damage is not severe. Public disclosure of medical malpractices originates in 1986th Health Act, which leads to National Practitioner Data Bank (NPDB). About 10 years later, Massachusetts was the first state which released the practitioners records on the web. By now, many states' medical boards are publicly reporting medical liability history.

There are two possible⁶ methods to address this concern: First, using National Practitioner Data Bank (1990-2014), one can show that the evolution of next med-mal is the same among FL and some other states-years in which the public disclosure of malpractice records are not passed (see Figure 2, Panel A)⁷. For example, NY passed the

⁶ Other response would be to compare the probability of being sued among physicians with unpaid prior claims and paid claims. Unfortunately, the available data to this study only corresponds to paid claims. It is not only in FL that insurers are not obligated to report unpaid claims, but the same rule exists in TX, IL (after 2006). Besides that, the NPDB encompasses only paid claims.

⁷ The patterns in FL and other states diverge as the number of prior med-mals increases (where the Law of Large Number is not valid due to Small Sample). That's why I exclude case-physicians with number of prior med-mals>6 in the robustness test (Table 10).

Bill in 2008. Once we restricts the NPDB to years<2008, the average probability of being sued for one more time is bigger in NY than in FL, in which public disclosure was passed and enforced from many years before 2008. The Wilcoxon test also indicates that the distribution of the probability of being sued is different in the two states, but it is rightly shifted in NY. As another comparison, IL passed the same Bill in 2009 with releasing the information for the past 5 years on the web. Again, the statistics doesn't show that physicians in IL are sued less than FL (before 2011). Wilcoxon test of having the same distribution cannot be rejected within 5%, and the average probability of being sued in FL is not significantly differs from IL' (Figure 2, Panel A). Therefore, there is no significant evidence that public disclosure incentivize patients to file lawsuit against priory litigated physicians.

As a second response to the concern on unobserved heterogeneity, one could measures the correlation between *history* and the variables which are more likely to be affected by sample selection hypothesis: *damage severity* and *payment*. If physicians with bad *history* are more likely to be litigated because of patients mistrust and not a real malpractice, then a negative correlation between either *severity/liability/payment* and *history* may exist. We cannot measure liability using FL dataset, but severity and payment are observed. Interestingly, the FL data rejects any correlation between the above mentioned variables: number of prior med-mals (*history*) doesn't explain any part of the current case's damage severity⁸. The same thing is true for the current payment,

⁸ In an older version of this paper I had reported the correlation between *total* number of med-mals and damage severity, which is negative. Total number of med-mals encompasses all the prior and **posterior** med-mals in physicians' life (while *history* encompasses only prior med-mals). It is obvious that patients don't know total med-mals at the time of the current litigation; therefore, the negative correlation between severity and *total* med-mals doesn't violate the rejection of sample selection bias in FL data.

suggesting that numbers of prior med-mals may not be endogenously derived by insufficient skills. Table A (below) summarizes the above reasoning:

Table A: Sample Selection in Data, Channels and Remedies

	Channels	How addressed in this study
Probability of being litigated is explained by number of prior med-mals (Studdert, et. al., 2016)	1. Physicians' skill (type)	using FE estimator
	2. Easier for Patients to defeat them	Comparing FL to other states Consistency with the data (see Table B)

Table B: Correlation Between History and the Current Case Specifications Under Different Hypotheses

	Under Learning Hypothesis	Under Selection of Priority Litigated Physicians by the Patients	Realized Impacts (robust to exclusion of right censored data and prior med-mals>6)
Corr(duration,history)	Negative	Negative	Negative
Corr(Litigation cost,history)	Negative	Negative	Negative
Corr(Damage Severity,history)	No effect	Negative	Insignificant
Corr(Payment,history)	No effect	Negative	Insignificant
Corr(liability,history)	No effect	Negative	Un-measurable

The learning literature mainly focuses on the consumers' purchasing decision in different experiences. i.e. they learn how to choose the best calling plan for themselves by observing cost differences between options (Miravete (2003)), or, the effectiveness of alternative drugs from prescription experience (Crawford & Shum (2005)). This paper adds to the literatures on learning and litigation. The learning evidence of this paper calls for a new mechanism to decrease litigation duration and cost, which might be of particular interest to policy makers. Medical malpractice litigations lead too long, expensive legal procedures and also create substantial loss to the tort system. Based on the findings of this study, providing information to those defendants who are not familiar with the legal procedure could save significant amounts of time and money. This paper proceeds as follows: in section 2, the FL dataset is described. In section 3, the theoretical model on divergent expectation is extended to a dynamic version; over multiple

litigations, agents update their beliefs; as a results, their private information would be drawn from distributions which are narrowing down. Section 4 describes the empirical results. Alternative hypothesis (sample selection and unobserved heterogeneity) are discussed in section 5 and robustness tests are reported in section 6. Final discussion is in section 7.

2. DATA

The dataset used in this study is taken from the Florida Office of Insurance Regulation. It includes 17,238 closed and pro-plaintiff (paid) med-mal claims with individual defendants in Florida⁹ for the years from 1994 to 2012¹⁰. The data encompasses over 13,675 case-physicians in which corresponding physicians are litigated for the first time. 11,075 of these physicians would not experiencing any other future (paid) med-mal, but 2,600 (19%) are involved in at least one more med-mal, 657 in at least two more med-mals, 175 in at least three more med-mals and 67 in more than three med-mals.

In addition to the numbers of prior med-mals and length of litigation, the dataset of this study contains other variables including payment, damage severity, defense spending, stage of dispute, and geometrical characteristics. Table 1 defines the variables and provides their statistics. Table 2 shows the different stages of litigation and the frequency of cases with similar closing stages.

Table 3 represents the length of the current litigations in number of days (*duration*) for different levels of *history* (number of prior med-mals) and *total med-mals*

⁹ This study excludes over 10,000 cases involving entities; in addition, over 100 cases with missing license numbers are dropped.

¹⁰ which is the most recent year of data available at the time of writing this study.

(sum of prior and posterior med-mals). A physician's *history* is the number of her previous malpractices that have been closed prior to the closing date of the current one. *Total med-mals* refers to the total number of malpractices in the individual's life cycle, which is available in the current dataset.

In all rows (in which level of total med-mals varies from 1 to 6), There exists a decreasing pattern on duration when number of prior med-mals increases (in columns). For example, on average, the first litigation of those physicians with total med-mals equal to 4 lasts 1,962 days; while their second litigation lasts 1,882 days, and their last one is 1,377 day long, which is about 60% of duration of their first litigation.

In addition to the above mentioned horizontal trend, Table 3 reveals a vertical increasing trend. According to the data, the first litigation lasts longer for those who have higher *total med-mals*. As an example, for someone with total of three med-mals, the first case lasts 2,006 days as compared to 2,277 days for someone with *total med-mals*= 5. While this trend is not the interest of this paper, it might be a good question for future studies to pursue.

Data Caveats: The FL dataset does not include open cases¹¹ (Insurers are obligated to report the closed and paid claims). Table 4 indicates numbers of claims by closing year and the year of injury. A dramatic decrease after 2004 could be explained by the right censorship: average med-mal litigation lasts several years (3.6 years in this

¹¹ There are other issues regarding FL dataset, same as all other states and NPDB: the following cases are NOT reported in those datasets: Pending malpractice cases, Cases the physician may have won on a technicality like the statute of limitations, Claims from when the physician practiced in any other state, Claims paid by the physician himself rather than malpractice insurance, Disciplinary actions brought by the State of Florida, Disciplinary actions by hospitals against the physician, Paid claims which were inadvertently not reported by an insurance company (we have personal experience with these), Claims against certain doctors when they were practicing at “teaching hospitals”.

dataset). Thus, censored cases cause a misrepresentation of med-mals in recent years. As a robustness test, cases closed in 2005 and later are excluded in Table 10 (Panel A).

The highest number of total med-mals in FL is 14 (this number exceeds 100 in NPDB). However, very few case-physicians are corresponding to very high number of prior med-mals. Therefore, to check the sensitivity of the main results to these cases, those are excluded in Table 10 (Panel A).

3. Model

This paper extends the divergent expectations (DE) model to include physicians with multiple malpractices. The standard DE model is a static bargaining model introduced by Priest and Klein (1984) and widely used in the litigation literature (i.e. Waldfogel (1995, 1998)). To capture the impact of learning, I develop a dynamic version of the DE model. The idea is that a defendant's belief about her current case is a perception that is updated based on prior experiences. A defendant with more numbers of med-mals ends up having a more realistic view towards the tort system.

The environment of the model is as follows: the amount of damage (M) is public information. True quality of the case (degree of liability) is Y , which is unobservable. However, a noisy signal of $Y=Y^*+\varepsilon^Y$, where ε^Y is a draw from a normal distribution ($N(0,\sigma^Y)$), is observable and considered as parties' estimate of the case quality. Note that both plaintiff and defendant utilize the same expectation about the quality of the case¹².

Despite the common Y , the parties disagree about the plaintiff's probability of winning. The court has an unobserved decision standard rule, called D^* , to which the

¹² Here I am simplifying the original DE model, in which the belief about the quality of the case is heterogeneous between the parties.

quality of the cases is compared. In other words, a pro-plaintiff verdict corresponds to claims in which quality of the case is bigger than court's decision standard, $Y^* > D^*$. Plaintiff and defendant have noisy but unbiased expectations about D^* , defined as $D_p = D^* + \varepsilon_p^D$ and $D_d^n = D^* + \varepsilon_d^{D,n}$, respectively. The error terms capture that agents' "initial" perceptions deviate from the true value, D^* . All the individual shocks are drawn from "mean-zero" Normal distributions: $\varepsilon^Y \sim \text{Normal}(0, \sigma^Y)$, $\varepsilon_p^D \sim \text{Normal}(0, \sigma_p^D)$, and $\varepsilon_d^{D,n} \sim \text{Normal}(0, \sigma_d^{D,n})$. Here, n , ($n \in \{1..N\}$) indicates physician's n th med-mal and N corresponds to the total number of a physician's med-mals.

$\sigma_d^{D,n}$ indicates how realistic is the physician, when she is handling her n^{th} med-mal. The bigger the $\sigma_d^{D,n}$, it is more likely to realize bigger error terms. However, experiencing a prior med-mal corresponds to observing an error term. Thus, the physician would update her belief about the distribution of the error terms based on her experiences. Therefore, $\sigma_d^{D,n}$ stands for the n th update of the distribution function of $\varepsilon_d^{D,n}$. It can be updated as following: $\sigma_d^{D,n+1} = \frac{\sigma_d^{D,n}}{1 + n\sigma_d^{D,n}/\sigma_d^D}$. Note that $\sigma_d^{D,n}$ is decreasing in n :

$$\frac{\Delta \sigma_d^{D,n}}{\Delta n} < 0 \quad (1)$$

Equation 1 states that the experienced physicians benefit from smaller standard errors $\sigma_d^{D,n}$, or, a more realistic point of view.

At the bargaining stage, the plaintiff demands $P_p M + C_p^S - C_p^t$, and the defendant offers $P_d M + C_d^S - C_d^t$, where C_i^S and C_i^t ($i \in \{p, d\}$) are the litigation costs of settlement and trial stages. The parties can settle if the plaintiff's demand is less than the defendant's offer:

$$P_p - C < P_d \quad (2)$$

where, $C = \frac{C_p^t + C_d^t - C_p^s - C_d^s}{M}$, $P_d = \Pr(Y > D_d) = \Phi\left(\frac{Y^* + \varepsilon_d - D^*}{\sigma_d^{D,n}}\right)$, $P_p = \Pr(Y > D_p) = \Phi\left(\frac{Y^* + \varepsilon_p - D^*}{\sigma_p}\right)$.

More definitions are as following: $\varepsilon_d = \varepsilon^Y - \varepsilon_d^{D,n}$, $\sigma_d^n = \sigma^Y + \sigma_d^{D,n}$, $\varepsilon_p = \varepsilon^Y - \varepsilon_p^D$, $\sigma_p^n = \sigma^Y + \sigma_p^D$.

Substituting the functional form of the distributions of shocks in equation 2, the condition for settlement can be obtained as $P_p - C < \Phi\left(\frac{Y^* + \varepsilon_d - D^*}{\sigma_d}\right)$. If the characteristics of the case (C) and the plaintiff's expectation (P_p) are fixed, the inequality is more likely to be valid when σ_d^n increases. In other words, more experienced defendants with less divergent expectation (smaller σ_d^n) are more likely to settle.

Empirical model: Based on the theoretical results, I propose an empirical approach to test the “learning hypothesis”. The theoretical model of this study suggests that more experienced physicians have more accurate expectations and larger settlement rates. Consequently, I can take advantage of “history” as a proxy for learning. In other words, α_s in the following model is expected to be negative:

$$Trial's Proxy = \alpha_s \times history + \gamma_s \times X + \varepsilon \quad (3)$$

where, *Trial's proxy* could be any proxy of insisting on litigation and not settling down: *duration* or *dummies for start of trial or suit filing* are good candidate. I continue with the *duration* as the main variable of interest. As in the empirical section, *history* is the number of a physician's previous malpractices, and X is a vector of observed case characteristics, which include plaintiff's gender, numbers of prior med-mals in same area, physician's speciality, damage severity and insurers' fixed effects on litigations. The last one captures heterogeneous settlement policies among insurers.

Duration is defined as the number of days that the case is open. The empirical model to test the learning hypothesis is as follows, in which we expect to observe a negative coefficient of history (α_d):

$$duration = \alpha_d \times history + \gamma \times X + \varepsilon \quad (4)$$

In addition, under the learning hypothesis, a more informed physician is more likely to avoid extra expenses. Therefore, we expect to estimate a negative impact of *duration* if *litigation cost* is replaced by *Trial Proxy* in model 3: $Litigation\ cost = \beta \times history + \gamma \times X + \varepsilon$.

4. Results

Duration (Table 5): In Table 5, results of equation (3) are reported using OLS and Fixed Effects (FE) estimators. Dependant variable is the *duration* of the current litigation. We are interested in coefficient of *history* (No. of prior med-mals) as an explanatory variables. When the data is pooled and OLS estimator is used, an increase in history significantly decreases duration by over 100 days (6% in 2nd column). In the FE estimator, physicians' fixed characteristics are controlled. The results indicates that is an individual physician has experienced one more litigation, her current litigation decreases by 382 days. If the damage is in her current litigation is permanent, the effect is pronounced and the duration decreases by 425 days. These are corresponding to 23%-24% when $\log(duration)$ is employed as the dependent variable.

Controlling Fixed Characteristics: Time trend is captured in all empirical models by year dummies. In addition, 229 insurers' dummies are included to capture effect of specific policies which are varying in different companies. In OLS frameworks, physicians' specialities are also captured by employing 284 dummy variables (These

dummies are not employed in FE regressions as speciality is assumed to be fixed over time).

Controlling Learning From Environment: If any experience has been carried over, it can also be among colleagues. Physicians may learn from other cases around them. To capture this effect, *Nmedmal-ziploc* is measured which accounts for the number of med-mals in the same zip code and location. *Nmedmal-ziploc* is included in all regressions as an explanatory variable.

Litigation costs (Table 6): Table 6 indicates the results of explaining *litigation cost* with *duration* and other explanatory variables. We expect the litigation cost to be lower for priory litigated physician if there is any learning effect, which is supported by results in Table 5. As results of the pooled OLS indicate, one more prior litigation cuts the current cost by \$10,274 (in constant \$2012) or 9% (for *log(litigation cost)* as dependent variable). After controlling individual characteristics in FE estimator, those effects are pronounced to \$29k (\$2012) and 27%.

Controlling for duration (Panel B of Table 6): Besides all the explanatory variables (*X*) discussed in Table 4, the *duration* is included (in Panel B) to capture the impact of number of opening days on cost. As shown in Panel B of Table 5, the impact of history on cost is still negative, albeit less significant. The impact shrinks to -3% (compare to -9% in Panel A) and -7% (compare to -27% in Panel B) in OLS and FE estimations, respectively.

5. Examining Alternative Hypotheses

Physicians Unobserved Type: One may be concerned whether the learning hypothesis is the main driving force of the results or something else, such as the physicians' quality and skills, referred to as *type*. According to this concern, unskilled physicians are more likely to be litigated. Moreover, they prefer to end litigations sooner because they are aware of their low chance of winning. Therefore, lacks of skills may result in a negative correlation between number of prior med-mals and duration of current litigation (equivalently, negative coefficient of history in Table 7).

Using the fixed effect specification captures physicians' heterogeneities which are constant in time. Results in Tables 5,6, 8 and 9 are robust to use of FE estimators, which indicate that unobserved physicians' type is not the driving force of the findings of this study, unless there is a dynamic unobserved skill or type that changes over time. One can hardly argue that a physician's skill may shrink over time. Therefore, if there is any unobserved skill that changes over time, it is an increasing one. If such an increasing trend in skills exists, the impact of *history* on *duration* is underestimated. Therefore, it is not a violation of the "learning hypothesis".

In addition to FE approach that addresses the concern about fixed unobserved heterogeneity, I argue that if a physician's skill is causing more med-mals or a bad history, then we expect her to be involved in cases with more severe damages. In other words, the physicians' history is expected to be positively correlated with the severity of damages. However, results in Table 8 counter this prediction: we cannot reject the null hypothesis of no correlation between *history* and damage *severity*.

Besides expecting a positive correlation between history and severity of damage (under a counter hypothesis derived by physicians' unobserved skill) the final payment

should be higher for physicians with prior med-mals. The reason is that, if having prior med-mals corresponds to easily being defeated, priory litigated physicians would lack bargaining power: first, they are aware of their weak performance, and second, their med-mal history is a public knowledge which is an additional pressure on them to settle. However, Table 9 indicates that we cannot reject the null hypothesis of no correlation between *history* and *payment*.

Sample Selection Bias: There is a concern whether physicians with a bad history are sued more. If this is true, the sample is biased towards weaker cases when number of previous med-mals increase.

A comparison between probability of next malpractice in states other than Florida suppresses sample selection bias. There are few ways to address this concern: 1) Within a rich dataset which encompasses both paid and zero paid cases, one compares the probability of next med-mal conditional on being verdicted in previous one: $H^0: \text{prob.}(\text{next med-mal} \mid \text{not verdicted}) = \text{prob.}(\text{next med-mal} \mid \text{verdicted})$. If the two probabilities are not significantly different, the dataset with only paid claims (case of this study) is a random draw of the overall population. 2) Comparison between probability of next med-mal in states with public and private history. If physicians cannot observe physicians' past history, their decision on filing suit is not conditioned on the information about previous malpractices. Therefore, states without public history can be used as the benchmark to which the Florida dataset should be compared. 3) By excluding *marginal cases* which are more likely to target a physician with bad reputation. Any med-mal case is determined with two unobserved heterogeneities: damage and liability; therefore,

a *marginal* case can be a case with just an emotional (low) damage or a low chance of proving physicians negligence.

Going through the first path requires a dataset with all paid and unpaid cases, which is not available in this study. The second test is possible to be done using the public dataset of National Practitioner Data Bank (NPDB). NPDB includes more than 270,000 observations over all US states, for reporting years between 1990-2014, from which, more than 20,000 cases are occurred in Florida. At each level of n^{th} malpractice, the probability of next malpractice is calculated as the ratio of number of physicians with $n+1^{\text{th}}$ malpractice divided by physicians with n^{th} malpractice. Probabilities (for number of med-mals<15) are shown in Table 11. The difference between probability of next med-mal in Florida and other states is -0.03 (ttest: -1.23). This result does not support the sample selection bias in Florida dataset.

The 3rd way to reject sample selection bias is not possible since we cannot identify both sources of randomness: damage and negligence. However, the sample could be restricted to cases with permanent damage, which exclude the possibility of marginal *damage* case. This is the main reason all specifications are tested in a restricted dataset which only encompasses med-mals with permanent damage. Results are robust to this restriction, too.

6. Robustness Check

As a robustness test, two dimensions of the dataset have been restricted. First, right censored data: med-mal cases take an average of four years to be resolved. This may create a considerable right censorship in the dataset of this study, which doesn't

include pending claims. Hence, a reasonable critique is that the results are derived by recent closed cases, which have a shorter duration than open ones which are not observed yet. In Table 4, numbers of occurred and closed cases per year are shown. As an ad-hoc method to exclude rightly censored data, 2004 is considered as the last year of the data.

Second, there are few case-physicians with very high number of prior med-mals. There is a concern whether those cases bias the results. On the other hand, ratio of permanent to all cases drops sharply when number of prior med-mals increases from 5 to 6 (see Table 7). In the Panel A of Table 10, the dataset is inclusive to the cases closed in year < 2005 and corresponds to history < 6. Results indicate that the main findings are robust to these changes.

7. Final Discussion

This study proposes a new determinant for litigation duration and tests it empirically. In particular, a learning mechanism is introduced in a dynamic DE framework as a theoretical motivation to explain the impact of prior med-mals on the current litigation duration. In the empirical section, it is documented that priory litigated physicians have shorter current litigation and burden less expenses. Many explanatory variables are controlled, including patients' gender, time dummies, specialty fixed effects, insurers' fixed policies, and learning from colleagues. Moreover, using Fixed Effect estimator, physicians' individual characteristics are also captured. The results are robust to many robustness tests.

Who has control over settlement? The learning hypothesis suggests an important question: who really manages the litigation process? Although there are some

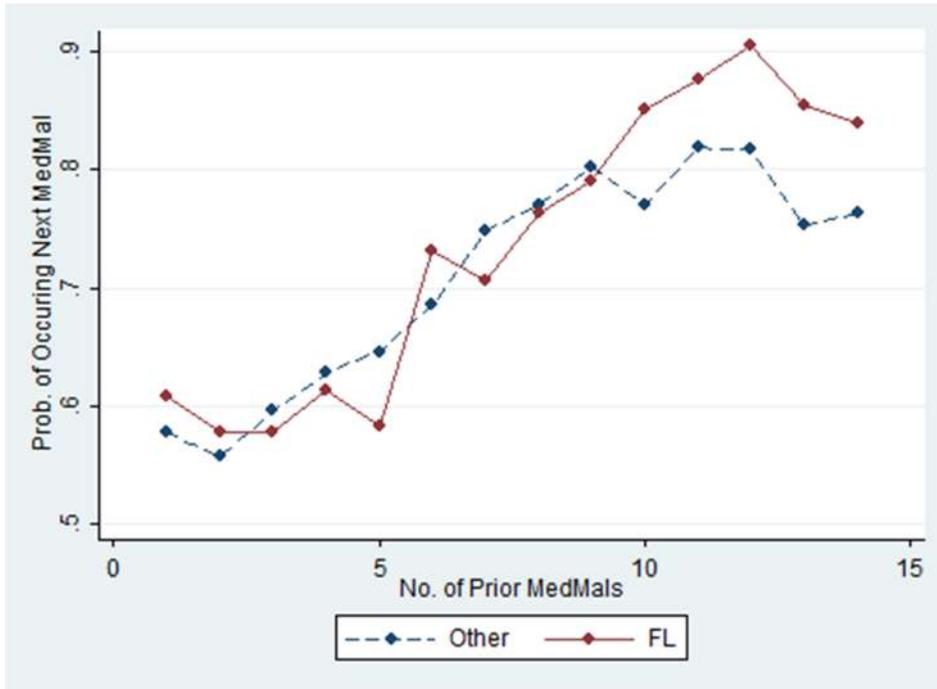
insurance contracts in which the physician has the right to reject the settlement, this does not apply to all of them. Hence, it is reasonable to ask who really learns from a physicians litigation history? Physicians who have malpractice experience are more likely to add the relevant legal term in their insurance contracts so that they can control the settlement. They are more familiar with the rules and perceive whether their insurers care about their reputations or not. In addition, although the conflict of interest between physicians and their insurers cannot be completely ignored, we may assume that they benefit from each others' information during the litigation process. Hence, even though insurers are formally controlling the case, they still can benefit from the physician's experience and involve them in settlement decisions and the learning hypothesis still applies. Future studies with a more detailed dataset can investigate this question.

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Figures and Tables

Fig 1: Probability of Next Med-Mal in Florida and Other States



Note: The content of Table 11 is plotted in this figure. Vertical axis is the average probability of occurring next medmal at each level of current number of medmals in FL and Other states. The maximum number of medmals which is documented for physicians is 247 (not shown here) in this data. Probability of next medmal is calculated as follows: at each level of history(No. of prior medmals), the ratio of physicians *with* a next medmal divided by the number of physicians. As an example, the first row of Table 11 indicates that in FL (other states), 60.8% (57.7%) of physicians who are not having any prior medmal (history=1) would involve in at least one more med-mal in future. Other states include: AL, AR, AZ,CA, CO, CT,DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, , MI, MN, MO, MS, MT, NC, NH, NJ, NM, NV, NY, OH, OK, OR, PA, PR, SC, TN, TX, UT, VA, WA,WI, WV. 19 other states with number of medmal cases<500 are excluded. 18,665 observations with missing work state are excluded. Data source is the National Practitioner Data Bank, with reporting year between 1990 to 2014.

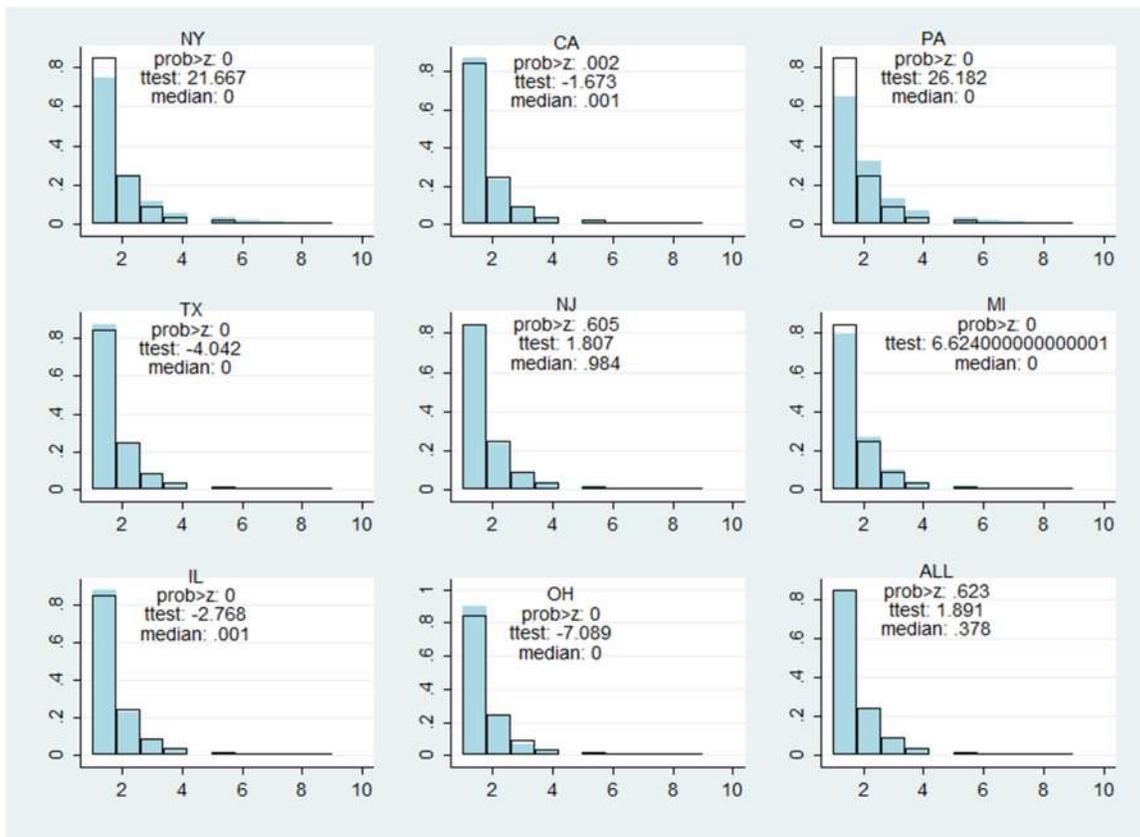
Fig 2: The Distribution of Number of Physician over Number of Med-Mals

Panel A: NPDB, Restricted to Years Before Public Disclosure is Passed

	The Bill on Public Disclosure of Medical Malpractices in Each of the Large States in NPDB	Restriction
NY	Passed in 2008 and publicly available on web	Restrict data to year<2008: P-value in Wilcoxon test=4E-20%, Diff. in mean (NY minus FL)=+0.13 (ttest=10.6)
IL	Passed in 2011, records of last 5 years are publicly available on web	For years<2011: P-value in Wilcoxon test=5.3%, Diff. in mean (IL minus FL)=-0.02 (ttest=-1.5)

Note: The table shows the test for difference between FL and other states' probability of being sued. For each state, the 1st column explains when the Bill on public disclosure of medical malpractices is passed. In the second column, after restricting data to mentioned years, FL and each of other states are compared with the null hypothesis of having the same distribution over probability of being sued conditional to number of prior med-mals.

Panel B: NPDB, 1990-2014 (All Available Years)



Note: Diagram show the difference between distribution of repeated med-mals in **FL (unfilled bars)** vs. **other states (solid bars)**, using NPDB. Horizontal axis shows number of med-mals. Vertical axis show frequencies of number of physicians which has the same number of med-mals in the data. The p-values in the Wilcoxon Mann-Whitney test (H0: the two distributions are the same) test and the t-statistics (to compare the mean of the two distributions) are reported. Cases with number of prior med-mals>10 are excluded. The NPDB used in here contains over 278,000 observations from 1990 to 2014; 20,000 med-mals are occurred in FL, and the top 8 states with highest number of med-mals are chosen for comparison: NY: 38852, CA: 29622, PA: 22093, TX: 18360, NJ: 11300, MI: 11156, IL: 10702, OH: 9653

Table 1: Data Description

	description	N	sum	mean	min	max	s.d.
ID	Insured ID	17,238					
History	Number of prior med-mals upto current med-mals	17,238	22,351	1.3	1	14	1
Accumulated History	Total number of med-mals for each defendant in the dataset	17,238	27,464	1.6	1	14	1
Duration	Number of days from occurrence to closing	17,238		1,577	30	8,820	746
Defense Spending	paid to the defense counsel	17,238		74,851	-	160,681,792	1,264,011
permanent	Permanent=1 if permanent damage	17,238	12,907	0.7	-	1	0
plaintiff's Sex	sex=1 if female	17,238	8,853	0.5	-	1	1
Permanent	Dummy for permanent damage	17,238	12,907	0.7	-	1	0

Note: Data description; source of data: Medical Malpractices in Florida, Florida Office of Insurance Regulation.

Table 2: Description of Litigation Stages

No. of Stage	Description of Stage.
0	Prior to suit being filed (more than 90 days before suit is filed)
1	Within 90 days of suit being filed.
2	More than 90 days, after suit filed and prior to or during the course of mandatory settlement conference.
3	During trial, but before court verdict.
4	After court verdict and prior to filing of notice of appeal.
5	After notice of appeal is filed or post judgement relief of action is required for recovery.
6	During appeal.
7	After appeal.

Note: Different stages of litigation.

Table 3: Average Duration for Different No. of Prior Med-Mals

Total Med-Mals	Number of Physicians	No. of Prior Med-Mals (History)					
		0	1	2	3	4	5
		Duration (No. of days from occurrence to closure)					
1	11,075	1,544					
2	1,943	1,789	1,424				
3	482	2,006	1,626	1,395			
4	108	1,962	1,889	1,530	1,377		
5	38	2,277	1,856	1,724	1,537	1,332	
6	15	2,314	1,784	1,762	1,777	1,324	1,270

Note: The table shows the average *duration* which is measured in number of days from occurrence to closure; columns are *number of prior med-mals (history)* at the time of the current case (for which the *duration* is reported). Rows are total number of med-mals for each physician. This fact is true for each category of physicians with different *total med-mals (ACCH)* (rows). The statistics are not shown for very few cases with number of prior med-mals > 6.

Table 4: Number of MedMals by Year

Panel A: No. of **Occurred** MedMals in Each Year Which are Closed by 2012

year	1994	1995	1996	1997	1998	1999	2000	2001	2002
#	1028	1012	1005	1005	1122	1434	1844	1811	1533
year	2003	2004	2005	2006	2007	2008	2009	2010	2011
#	1232	1020	896	717	651	393	171	46	3

Panel A: No. of **Closed** MedMals in Each Year

year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
#	6	52	183	503	696	688	835	853	943	1157
year	2004	2005	2006	2007	2008	2009	2010	2011	2012	
#	1782	1799	1640	1438	1311	1200	1059	975	49	

Note: Number of claims which are occurred (panel A) and closed (panel B) in different years. All the claims are closed (no open case is reported to FL Insurance Department). Years before 1994 are dropped due to different data quality. Grey cells shows part of the data which is excluded in the robustness test.

Table 5: The Impact of No. of Prior MedMals (History) on Duration

	OLS		Panel Data with Physicians' Fixed Effects			
	All Cases		All Cases	permanent damage Cases	All cases	permanent damage Cases
<i>Dependent variable</i>	duration	Ln(duration)	duration		Ln(duration)	
History (no. of prior medmals)	-107 (14.8)**	-0.06 (12.2)**	-382 (11.8)**	-425 (23.0)**	-0.23 (12.0)**	-0.24 (24.3)**
Permanent damage	9.537 -0.7	0.031 (3.4)**	-11.198 -0.5		0.008 -0.6	
Insurers fixed effects (229 dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for Specialty codes (284 dummies)	Yes	Yes				
No. of observations	16143	16143	17237	12907	17237	12907
R ²	0.2	0.2	0.5	0.5	0.4	0.5
No. of physicians			13674	10712	13674	10712

Note: The impact of number of prior medmals on duration of the current case, using OLS and fixed effect specifications. In FE regressions, fixed characteristics of each physician are controlled. Dependent variables are duration (or numbers of opening days) and its logarithm. All regressions include the following explanatory variables: constant term, plaintiff sex, number of prior medmals in the same zip code area and same specialty code, dummies for year, 228 dummies for insurer companies and constant term. Regressions within the *All Cases* also include dummy for permanent damage. The OLS regressions include 217 dummies for physicians specialty codes. Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 6: The Impact of Prior MedMals (History) on Litigation Costs

Panel A

	OLS		Panel with Physicians' Fixed Effects			
	All cases		All cases	permanent damage Cases	All cases	permanent damage Cases
<i>Dependent variable</i>	cost	Ln(cost)	cost		Ln(cost)	
History (no. of prior medmals)	-10,274 1.3	-0.098 (6.7)**	-22,285 (3.4)**	-29,314 (3.4)**	-0.221 (5.8)**	-0.27 (10.6)**
Permanent damage	41,809 (2.1)*	0.427 (16.8)**	16,394 (3.1)**		0.344 (7.5)**	
Insurers fixed effects (229 dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for Specialty codes (284 dummies)	Yes	Yes				
No. of observations	16143	14966	17237	12907	15959	12038
R ²	0	0.2	0.1	0.1	0.2	0.2
No. of physicians			13674	10712	12791	10067

Panel B: Including *Duration* as Explanatory Variable

	OLS		Panel Data with Physicians' Fixed Effects			
	All Cases		All Cases	permanent damage Cases	All cases	permanent damage Cases
<i>Dependent variable</i>	duration	Ln(duration)	duration		Ln(duration)	
History (no. of prior medmals)	-5,146 -0.7	-0.036 (2.5)*	-14,539 -1.1	-25,730 -1.3	-0.012 -0.4	-0.073 (2.3)*
Permanent damage	41,355 (2.0)*	0.429 (18.1)**	16,621 (3.2)**		0.359 (8.2)**	
Duration	47 (5.5)**	0.001 (39.2)**	20 -1.1	8.4 -0.3	0.001 (12.0)**	0.0004 (8.8)**
Insurers fixed effects (229 dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for Specialty codes (284 dummies)	Yes	Yes				
No. of observations	16143	14966	17237	12907	15959	12038
R ²	0	0.3	0.1	0.1	0.2	0.2
No. of physicians			13674	10712	12791	10067

Note: The impact of number of prior medmals on cost of current litigation, using OLS and fixed effect specifications. In FE regressions, fixed characteristics of each physician are controlled. Dependent variables are litigation cost and its logarithm. All regressions include the following explanatory variables: constant term, plaintiff sex, number of prior medmals in the same zip code area and same specialty code, dummies for year, 228 dummies for insurer companies and constant term. Regressions within the *All Cases* also include dummy for permanent damage. The OLS regressions include 217 dummies for physicians specialty codes. Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 7: Damage Severity for Pools of Physicians with the Same Number of Prior Med-Mals

No. of Prior Med-Mals	Number of Physicians-cases	Ratio of Permanent to All Cases
1	13675	.75
2	2600	.76
3	657	.72
4	175	.69
5	67	.70
6	29	.52
7	14	.64
8	8	.37
9	6	.67
10	3	0.33

Note: Table shows the ratio of permanent to all cases for different pools of physicians-cases in which the number of prior med-mals are the same. For example, row 3 should be read as this: there are 657 cases in which their corresponding physician has 3 prior med-mals; Also, in 72% (out of 657) cases the damage is permanent. Grey area shows the part of data which is excluded in the robustness test (Table 10). There are 4 case-physicians with number of prior med-mals between 10 and 14, which are not shown in this table.

Table 8: The Impact of Prior MedMals (History) on Damage Severity

	OLS	Panel with Physicians' Fixed Effects	
	All cases	All cases	Only permanent damage Cases (5-9)
<i>Dependent variable</i>	Damage Severity (from 1 to 9)		
History (no. of prior medmals)	-0.003 -0.2	0.014 -0.6	0.026 -0.7
Permanent damage	4.076 (161.4)**	3.862 (64.2)**	
Insurers fixed effects (229 dummies)	Yes	Yes	Yes
Dummy for Specialty codes (284 dummies)	Yes		
No. of observations	16143	17237	12907
R ²	0.7	0.6	0.1
No. of physicians		13674	10712

Note: The impact of number of prior medmals on damage severity of current litigation, using OLS and fixed effect specifications. Damage severity is a number from 1 to 9, with the following descriptions; 1: emotional damages, 2: slight temporary damages, 3: minor temporary damages, 4: major temporary damages, 5: minor permanent damages, 6: significant permanent damages, 7: major permanent damages, 8: grave permanent damages, 9: death. In FE regressions, fixed characteristics of each physician are controlled. All regressions include the following explanatory variables: constant term, plaintiff sex, number of prior medmals in the same zip code area and same specialty code, dummies for year, 228 dummies for insurer companies and constant term. Regressions within the *All Cases* also include dummy for permanent damage. The OLS regressions include 217 dummies for physicians specialty codes. Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 9: The Impact of Prior MedMals (History) on Payment

	OLS		Panel with Physicians' Fixed Effects			
	All cases		All cases	permanent damage Cases	All cases	permanent damage Cases
<i>Dependent variable</i>	pay	Ln(pay)	pay		Ln(pay)	
History (no. of prior medmals)	-22,368 -0.6	-0.021 -1.4	19,049 -1.4	30,314 -1.2	-0.011 -0.4	-0.025 -0.7
Permanent damage	254,494 (2.1)*	0.902 (26.5)**	121,632 (8.0)**		0.768 (9.5)**	
Insurers fixed effects (229 dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for Specialty codes (284 dummies)	Yes	Yes				
No. of observations	16059	10478	17132	12838	11239	8729
R ²	0	0.2	0	0	0.2	0.2
No. of physicians			13613	10667	9553	7676

Note: The impact of number of prior medmals on payment of current litigation, using OLS and fixed effect specifications. Payments are in 2012 dollar using US Consumer Price Index. In FE regressions, fixed characteristics of each physician are controlled. Dependent variables are payment and its logarithm. All regressions include the following explanatory variables: constant term, plaintiff sex, number of prior medmals in the same zip code area and same specialty code, dummies for year, 228 dummies for insurer companies and constant term. Regressions within the *All Cases* also include dummy for permanent damage. The OLS regressions include 217 dummies for physicians specialty codes. Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 10: Sensitivity Analysis

Panel A: Restricted Data

s	OLS		Panel with Physicians' Fixed Effects			
			All cases	permanent damage Cases	All cases	permanent damage Cases
<i>Dependant Variable</i>	w/ Log transfer		w/ Log transfer			
<i>Duration</i>	-168 (12.6)**	-0.117 (10.6)**	-390 (18.2)**	-430 (14.6)**	-0.27 (20.6)**	-0.29 (17.7)**
<i>Litigation Cost</i>	-41,060 -1.3	-0.15 (4.7)**	-10,332.40 (4.8)**	-14,519.57 (4.1)**	-0.245 (5.2)**	-0.32 (4.9)**
<i>Severity</i>	0.004 -0.1		0.028 -0.4	-0.012 -0.1		
<i>Payment</i>	-189,243 -1	-0.047 -1.1	12,673.86 -0.8	16,431 -0.8	-0.011 -0.1	0.004 0

Note (Panel A): The table summarizes the results within the restricted dataset. Each cell belongs to a different regression in which dependent variables are: Duration, Litigation cost, severity and Payment. Estimated coefficients of *history* are reported. Only cases-physicians with number of prior med-mals < 6 are included. Also, cases which are closed after 2004 are excluded in order to address the right censorship, which is shown in Table 4.

Panel B: Main Data (Repeated For Fast Looking Comparison)

	OLS		Panel with Physicians' Fixed Effects			
			All cases	permanent damage Cases	All cases	permanent damage Cases
<i>Dependant Variable</i>	w/ Log transfer		w/ Log transfer			
<i>Duration</i>	-107 (14.8)**	-0.06 (12.2)**	-382 (11.8)**	-425 (23.0)**	-0.23 (12.0)**	-0.24 (24.3)**
<i>Litigation Cost</i>	-10,274 1.3	-0.098 (6.7)**	-22,285 (3.4)**	-29,314 (3.4)**	-0.221 (5.8)**	-0.27 (10.6)**
<i>Severity</i>	-0.003 -0.2		0.014 -0.6	0.026 -0.7		
<i>Payment</i>	-22,368 -0.6	-0.021 -1.4	19,049 -1.4	30,314 -1.2	-0.011 -0.4	-0.025 -0.7

Note (Panel B): The table summarizes results in Tables 5,6,8 and 9. Each cell belongs to a different regression in which dependent variables are: Duration, Litigation cost, severity and Payment. Estimated coefficients of *history* are reported

Note (both panels): The impact of number of prior medmals on different characteristics of the current litigation, including duration, litigation cost, damage severity, and payment. Payments are in 2012 dollar using US Consumer Price Index. Damage Severity is indexed from 1 to 9 with 1 corresponds to just emotional and 9 to death cases. In FE regressions, fixed characteristics of each physician are controlled. All regressions include the following explanatory variables: constant term, plaintiff sex, number of prior medmals in the same zip code area and same specialty code, dummies for year, 228 dummies for insurer companies and constant term. Regressions within the *All Cases* also include dummy for permanent damage. The OLS regressions include 217 dummies for physicians specialty codes. Robust t statistics in parentheses. * significant at 5%; ** significant at 1%.

Table 11: Data Evaluation

number of medmals	Average prob. of next medmal in other states	prob. of next medmal in Florida	difference
1	0.577	0.608	0.031
2	0.557	0.578	0.022
3	0.596	0.577	0.019
4	0.628	0.614	0.014
5	0.646	0.582	0.064
6	0.686	0.732	0.046
7	0.748	0.706	0.043
8	0.771	0.764	0.006
9	0.802	0.790	0.012
10	0.771	0.851	0.080
11	0.819	0.876	0.057
12	0.817	0.906	0.089
13	0.753	0.854	0.100
14	0.763	0.840	0.077

Note: Table shows the average probability of occurring next medmal at each level of current number of medmals. The maximum number of medmals which is documented for physicians is 247 (not shown here) in this data. Probability of next medmal is calculated by the ratio of physicians with a next medmal divide by number of physicians at current level. As an example, the first row indicates that if a physician has only 1 medmal, probability of 2nd medmals would be 60.8% (57.7%) if she is in Florida (other states). Other states include: AL, AR, AZ, CA, CO, CT, DC, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, , MI, MN, MO, MS, MT, NC, NH, NJ, NM, NV, NY, OH, OK, OR, PA, PR, SC, TN, TX, UT, VA, WA, WI, WV. 19 other states with number of medmal cases < 500 are excluded. 18,665 observations with missing work state are excluded. Data source is the National Practitioner Data Bank, with reporting year between 1990 to 2014.

