Medical Malpractice and the Adoption of Medical Technology

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May 15, 2015

1 Introduction

A successful medical malpractice lawsuit must demonstrate the following:

1. The defending physician had a professional duty to the plaintiff
2. The patient experienced an injury or negative outcome
3. The physician’s actions were directly responsible for the patient’s injury
4. The physician’s actions failed to meet the standard of care

Medical malpractice lawsuits rarely focus on the first three elements above (Greenburg 2009). The final element - standard of care - is the center point of most litigation. The disagreement surrounding standard of care in civil proceedings relates to the fact that it exists as a concept rather than strict definition. The defending physician must demonstrate that he or she acted reasonably given the clinical context and that other physicians would have acted similarly. This implies that physicians are incentivized to maintain practice patterns that are similar to those of their peers.

The current medical malpractice literature considers the physician-litigation relationship in the context of defensive medicine: routine use of testing and procedures whose benefits do not justify costs. At best, defensive medicine represents "flat of the curve"\(^1\) spending by physicians who hope to minimize negative outcomes altogether. At worst, defensive medicine provides no demonstrable benefit to patient outcomes but, in retrospect, supports a physician’s claim that his workup and treatment approaches were more than adequate. Invariably, the hypothesized relationship between malpractice pressure and defensive medicine is monotonic - greater malpractice equates to greater defensive practices.

This paper proposes a second mechanism by which malpractice may influence physician practice: adoption of medical technology. By definition, a technology cannot be considered standard of care early in its diffusion process. Should a negative outcome arise, an early-adopting physician may be found liable for violating normal clinical practices. Thus, during this period, increasing malpractice should discourage adoption. As the diffusion process continues,\(^1\)

\(^1\) marked by large expenditures for relatively little gain in health outcomes
the technology eventually reaches a level of utilization commensurate with the incumbent treatment, marking a point when both approaches are reasonable. With further uptake, the technology becomes standard of care. After this point, increasing malpractice should encourage adoption.

This dissertation is organized as follows: I begin with a background review of diffusion of technology with special attention regarding the adoption of medical technology. Next, I construct a model of physician choice given levels of malpractice and adoption of these technologies. Next, the data sources are detailed followed by a description of the empirical specifications employed. The results of these models are presented in the following section. The dissertation then concludes with a discussion of the results and limitations.

2 Background

2.1 Malpractice

The relationship between medical malpractice and medical decision making has been studied extensively. Classically, malpractice pressure is thought to stimulate the practice of defensive medicine - increased spending by physicians on diagnostic testing in an attempt to reduce negative or unforeseen outcomes, thereby mitigating threats of malpractice. Because neither the physician nor the patient are fully responsible for the cost of these tests, they are obtained even if the patient benefit is trivial. These practices may result in equilibria in which marginal benefits differ substantially from marginal costs. Numerous studies have explored this relationship (Studdert, Mello 2005). Kessler and McClellan (1996) demonstrate large decreases in medical expenditures without significant changes in health outcomes associated with tort reform. Rates of procedures such as cesarean section (Localio 1993; Dubay 1999) seem to be influenced as well. In all contexts involving defensive medicine, the relationship between malpractice pressure and physician decision-making involve established practices and are monotonic.

The relationship between malpractice and diffusion of medical technology is not well described. Cutler and McClellen (1996) investigated six possible determinants of the diffusion of technologies to treat heart attacks; among these was malpractice climate. They included a variable which captured malpractice reform but the associated coefficients were small and statistically insignificant. These findings are, however, entirely possible given that reforms take place at different times in different states. If the relationship between these variables is in fact non-monotonic, the effects of early reform in one state may nullify those of later reforms in another.

2.2 Diffusion of Technology

If medical malpractice does influence medical decision making in an important way, it may affect the decision of whether to adopt a particular technology.
There is a rich literature exploring the general adoption of technology beginning with Griliches’ (1957) exploration of how diffusion of hybrid corn occurred. Griliches explanation focused on economic incentives. Differential uptake by individuals could be explained by differences in profitability by adopting farmers. Around the same time, a second school of thought championed sociological factors in the uptake of new technology. Specifically, the importance of social networks and characteristics of the individual and channels of communication (Rogers 1962) were stressed. Hall (2004) presents a comprehensive history of these two approaches to diffusion. The literature investigating diffusion of medical technology has historically focused on the importance of sociologic factors. Coleman, Katz, and Menzel (1957) provide the seminal example. They demonstrate that diffusion of a novel antibiotic was closely tied with the strength of a physician’s network amongst other physicians. Subsequently, the dependence of physician adoption patterns on that of peers has been documented in other areas (Burke, Fournier and Prasad 2005; Berndt, Pindyck, and Azoulay 2003). The explanation for what drives diffusion within networks is less clear.

A physician’s decision to adopt a new technology entails both risk and effort. Novel methods of diagnosis and treatment are, at best, unfamiliar. At worst, some technologies may actually be dangerous depending on the level of data supporting their use (Lasser 2002). Even after the safety and efficacy of a new technology has been established, the transition requires additional effort (dosing and side effects (Souvek 2014), interpretation of test results, acquisition of procedural skills - learning curve with laparoscopic cases (Dirksen 1996 and Agresta 2004). These costs may be mitigated by benefits. There is ample evidence that physicians derive utility from positive patient outcomes (Applegate 1986; Gallagher 2003; Lopez 2009). While outcomes may provide a high degree of intangible satisfaction, the threat of litigation provides significant direct incentives to adhere closely to the prevailing standard of care.

2.3 Standard of Care and Social Interaction

Standard of care is first described in the case of Richie vs. West, 1860 2:

When a person assumes the profession of physician and surgeon, he must . . . be held to employ a reasonable amount of skill and care. While he is not required to possess the highest order of qualification, to which men attain, still he must possess and exercise that degree of skill which is ordinarily possessed by members of the profession and whether an injury results from a want of skill or the want of its application, he will, in either case, be equally liable.

Essentially, physicians are required to provide a level of care that would be deemed adequate by their peers. Despite being the earliest known interpretation of this law, the tenants of this opinion have endured. More recently, Greenberg (2009) discusses the process of defining adequate care. Traditionally, the law has been very deferential to customary practice; whatever constitutes usual care in a region is often formally defined as reasonable conduct for that region. Thus, different regions may have different standards of care. This high-

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2Incidentally, Dr. West was represented by then practicing attorney Abraham Lincoln
lights the importance of networks in the diffusion of medical technology. It also implies that the degree of utilization of a technology may proxy for whether it could be reasonably considered standard of care. Finally, it underscores the dynamic nature of medical practice: the standard of care does not remain static. In fact, Williams (2004) argues that once a technology becomes widely adopted, physicians can be negligent in deferring its adoption. Significant case precedents now underscore this responsibility including Nowatske v. Osterloh (scleral buckling), Gates v. Fleischer (treatment of uterine ulcers), Burton v. Brooklyn Doctors Hospital (oxygen therapy for premature infants).

Because medical tort law defers, in some capacity, to customary practice, physicians are incentivized to maintain practice patterns that resemble those of their peers. Thus, the utility that a physician gains from a technological advance depends on factors inherent to the technology itself as well as its use by other physicians. Given this dynamic, this paper employs a model of social interaction in order to explain this relationship. Models of social interaction are distinguished by agent preferences that depend on the actions of a reference group. Agents respond to both changes in fundamentals and to the actions of the group. In aggregate, these indirect effects result in a social multiplier. Models of social interaction have become important tools for modeling discrepancies in outcomes despite initially similar endogenous variables and have been applied to a wide range of topics including conspicuous consumption patterns (Vleben 1934), segregation (Schelling 1971; Card, Mas, Rothstein 2008), crime (Glaeser, Sacerdote, and Scheinkman 1996), and technological adoption.

I frame the relationship between the diffusion of medical technology and medical malpractice in the context of social interaction. A technology in its infancy by definition would not qualify as standard of care. The decision to adopt and utilize a novel technology, therefore, entails risk on the part of the practitioner. Should a poor outcome or injury ensue, the practitioner faces greater scrutiny regarding whether utilization of this technology fell within commonly understood standards of care. This in addition to the relative dearth of information regarding a young product’s efficacy further enhances the importance of standard of care. At some point during a technology’s process of diffusion, adoption reaches a level of utilization that allows both the previous and novel technologies to be considered standards of care simultaneously. The possibility of equilibrium exists at this point but it is inherently unstable. After this point, the technology becomes standard of care while the previous modality loses this distinction.

In the next section, I construct a model that formalizes the relationship between malpractice and the adoption of medical technology. I demonstrate that if physician utility depends in part on the adoption decisions of others, the effect of malpractice changes after a technology becomes standard of care. In addition, I demonstrate that variance in uptake between hospitals should be lower in states with high malpractice pressure.

Empirically, I employ four novel, minimally-invasive surgical procedures as the basis for the empirical strategy. These include the application of laparoscopic technology to three surgical procedures - appendectomy, hysterectomy
and adhesiolysis. In addition, I consider the diffusion of endovascular approaches to vascular disease. In each case, the physician chooses between the technology (laparoscopic or endovascular) or the incumbent modality (open approach). I use a regression discontinuity specification to test for changes in the relationship between malpractice pressure and adoption. After normalizing adoption levels to the eventual equilibrium rate, I find that nearly all technologies experiencing an early period where adoption is discouraged by malpractice pressure followed by a period where malpractice facilitates diffusion. These results appear to be robust to the inclusion of a variety of variables controlling for insurance status, type and income. I also test for the relationship between malpractice pressure and procedure variance at the state level.

This dissertation finds that medical malpractice pressure influences physicians' decisions to adopt medical technologies. Furthermore, this effect appears to be non-monotonic, inhibiting adoption early then promoting it during the later stages of diffusion. The mechanism for this finding invokes the physician's perception of standard of care, the actions of his colleagues and deviation from which results in exposure to malpractice risk.

3 Model

3.1 Adoption Level and Malpractice Pressure

Our model employs physician learning within the context of a discrete choice framework. Learning models assume that consumers have limited information about products initially and update their beliefs with increasing experience. Erdem and Keane (1996) initially employed this approach to describe the influence of marketing campaigns on sales of consumer goods. Given its obvious application to adoption of medical technology, learning with discrete choice has been widely employed to describe the dynamics of diffusion. Coscelli (2004), Chan and Narasimhan (2013) and Ferreyra and Kosenek (2011) use prescription data to model a process by which physicians update their beliefs about the quality of a novel drug based on their cumulative experience with that technology. This literature typically focuses on modeling the process by which beliefs are updated. This paper borrows from the basic framework of these learning models. I employ a model by which physicians update their beliefs regarding the quality of a technology each period and compare those with their assessment of the incumbent practice.

I begin with a discrete choice template wherein the physician makes a decision \( d \in \{c, i\} \) between the current modality \( c \) or to adopt the innovation, \( i \), each conveying benefits \( B^d \) and malpractice costs equal to \( C^d_s \) which are specific to state \( s \). Because the incumbent technology has reached equilibrium, I assume its benefits to be well known and static with respect to time. The benefits of the incumbent practice are known and follow a fixed distribution across physicians:

\[
B^c \sim D(\mu, \sigma)
\]

\(^3\)removal of scar tissue from the abdomen for patients suffering bowel obstructions
With regards to the technology, physicians learn about benefits through a variety of mediums including personal experience, peer-reviewed articles, professional conferences, corporate marketing, and the experience of peers within a physician’s professional network. In contrast to the incumbent, the technology is novel. Therefore, knowledge of its benefits evolves with time.

\[ B_i^t \sim D(\mu_t, \sigma) \]

Thus, the net benefit of the technology is the difference between the benefits associated with the incumbent and the technology:

\[ B_i^t - B^c \sim D(\mu_t, \sigma) \]

This paper abstracts from formal mechanisms through which the learning process occurs, instead assuming that a learning process does occur. I assume that, in each period, agents receive new information and update their beliefs regarding the benefits of the technology. Thus, the net benefit of the technology is time dependent.

Malpractice costs vary based on whether the physician chooses current practice or innovation. Given that the physician’s choice is more likely to be considered standard of care if other physicians make the same choice, the probability of a successful lawsuit varies with the level of adoption of that technology at time \( t \) (\( a_t \in (1, 0) \)). Because the adoption level of a technology evolves with time, the malpractice costs associated with the technology and incumbent practice are time dependent as well. To simplify notation, I will suppress time subscripts from both adoption and malpractice costs. I define the expected malpractice costs as the probability of lawsuit multiplied by the average lawsuit size \( M_s \) for state \( s \). Thus the malpractice costs associated with the innovation:

\[ p(a)M_s = C_s^i \]

\[ \frac{d}{da} p(a) < 0 \]

The probability of lawsuit when the current practice is employed is inversely related to the adoption level of the technology:

\[ p(1 - a)M_s = C_s^c \]
Define $\theta^d_s$ as the difference between the benefit and cost associated with a given choice:

$$\theta^d_s = B^d - C^d$$

the agent will choose to adopt if

$$\theta^x_s - \theta^c_s > 0$$

$$\implies B^x_t - B^c_t > C^x_s - C^c_s$$

adoption is deferred otherwise.

Costs are restricted to malpractice costs. Benefits of the technology and the incumbent practice are exogenously determined and largely responsible for the equilibrium levels of adoption. At $t = 0$, the physician assessment of the technology’s quality $B^t_t$ is distributed according to some prior and updated each period as more information becomes available. I will explore three equilibrium benefit levels of interest: $B^t_t < B^c_t$, $B^t_t > B^c_t$ and $B^t_t >> B^c_t$. In the following sections, I vary the equilibrium rate of diffusion in order to explore the dynamics of malpractice on adoption. I focus first on the last inequality.

### 3.1.1 Diffusion of Technology Approaches 100%

I first explore the scenario in which net benefits associated with the technology are sufficient to allow 100% diffusion. As $a$ moves from 0 to 100% it progresses from novel to standard of care. Define $a^*$ as the level of adoption at which the two practices are considered equivalent. Since the treatments are considered equal, their corresponding malpractice risks are also equivalent:

$$p(a^*) = p(1 - a^*)$$

Similarly, at levels below this, $a^l$, the technology is a malpractice liability.

$$p(a^l) > p(1 - a^l)$$

Once adoption surpass this level, $a^h$, adoption becomes protective from malpractice.

$$p(a^h) < p(1 - a^h)$$

Now consider the state specific net malpractice cost, $C_s$, equal to the difference between the cost of the technology and the cost of the incumbent:

$$\frac{d}{da}p(1 - a) > 0$$

Because our explicit interest pertains to malpractice, other costs which might include time associated with skill acquisition, capital costs, measures of risk aversion, etc. are incorporated into the benefits term. This approach is reasonable given that all components of this model are additive. Therefore, specific labeling becomes arbitrary.
\[ [p(a) - p(1 - a)] M_s = C_s \]

Change in net malpractice cost associated with changes in malpractice therefore depends on adoption level.

\[ \frac{d}{dM_s} [p(a^l) - p(1 - a^l)] M_s > 0 \]

\[ \frac{d}{dM_s} [p(a^h) - p(1 - a^h)] M_s < 0 \]

At low levels of adoption, raising malpractice pressure raises net malpractice costs, therefore making adoption less likely by those utilizing the incumbent practice. High malpractice pressure illicits the opposite effect when diffusion has progressed past \( a^* \); greater liability decreases the threshold necessary for agents to choose adoption. Thus, adoption levels will be higher within the high malpractice states later in the diffusion process.

The dynamics of this model are illustrated in Figure 1. The adoption decisions over time are simulated for 100,000 agents practicing within a state having either severe (blue) or moderate (red) malpractice pressure. In each case, the mean and distribution of the incumbent’s benefits are static and equal across both states. Mean benefits corresponding to the technology increase by one unit each period. Variance of benefits remains constant over time and both mean and variance are equal across states.

Malpractice costs are equal to the probability of a successful lawsuit multiplied by malpractice severity. Severity varies between the two states; in this case, I vary malpractice severity by 50% which reflects the empirical difference between states at the 25th and 75th percentile. Probability of lawsuit is inversely proportional to the adoption level of the prior period and varies in absolute value from 0.001 to 0.01, an interval that reflects the empirical propensity of lawsuits across states.

In each period, each agent draws from the benefit distributions of both the incumbent and technology. Each choice also has its associated malpractice cost which depends on its utilization level and the malpractice severity of that state. For the simulation in Figure 1, adoption is determined at the national level by taking the mean level of utilization across both states. In addition, benefits associated with the technology are assumed to vastly exceed those of the incumbent practices as time progresses meaning that utilization levels of the technology approach 100% over time. In the following sections, I explore the dynamics of incomplete diffusion and how these are altered by state vs. national benchmarking.
Figure 1: Simulated diffusion curves in high and low malpractice climates. Distribution of benefits are equally distributed in both states whereas malpractice severity is greater in the blue states. The model predicts that raising malpractice pressure suppresses adoption initially. As diffusion progresses, malpractice risk associated with adoption decreases and a point is reached where growth within the high malpractice state exceeds that of the low malpractice state. Growth in the high malpractice climate persists, eventually reaching a greater overall level of adoption. Thus, raising malpractice pressure results in lower levels of utilization initially, higher levels of growth in the middle of the diffusion curve and higher overall levels of adoption later.
3.1.2 Incomplete Diffusion and State vs. National Benchmarking

Empirically, certain technologies never achieve complete diffusion. Extending the above model for diffusion to less than 100% utilization, we begin with the assumption that the net benefit of the technology reaches some limit well within the distribution of benefit conferred by the current technology. Arbitrarily, assume \( \lim_{t \to \infty} B_t^i - B^c \in (\mu^c - \epsilon, \mu^c + \epsilon) \) with \( \epsilon < \sigma^c \).

I first examine the dynamics of this relationship when \( B_t^i - B^c \to \mu^c - \epsilon \) which implies that the net benefit of technological adoption is less than that of the current technology. If we assume symmetric distributions of \( B_t^i \) and \( B^c \), then for periods in which \( \mathbb{E}[B_t^i] - \mathbb{E}[B^c] < 0 \), net benefits steer adoption levels to below 50%. I will assume that an adoption level of 50% represents the point at which \( C^i_t = C^c_t \) and is thus of particular importance with regards to physician decision making. Because adoption levels begin at 0, \( p(a) > p(1 - a) \) dictates that malpractice costs at adoption levels less than 50% will be greater for the technology than for the current practice and that these costs will be greatest in high malpractice environments. Furthermore, for all adoption levels below 50%, adoption rates within low malpractice states will exceed those of high malpractice states and these differences will persist over time as demonstrated in Figure 2.

The perceived benefits of some technologies will eventually exceed those of the incumbent. At some \( \mathbb{E}[B_t^i] - \mathbb{E}[B^c] > 0 \), adoption within the low malpractice state reaches 50%. As mentioned above, this level is of particular importance because it marks the first time that net malpractice costs will favor adoption of the innovation for both states. An adoption level of 50% accentuates adoption for all states but particularly for high malpractice climates. As mentioned above, the low malpractice states will attain this threshold first, meaning that for some period of time, adoption rates in the low state will exceed 50% while that in the high state will remain below. However, if malpractice probability is benchmarked at national levels of diffusion, physicians in both states will perceive the same benefits as well as the same probability of lawsuit. Only malpractice severity differs, with \( M_h > M_l \). Because malpractice severity enhances adoption once levels exceed 50%, utilization within the high malpractice states will eventually overtake that within low states. Furthermore, these differences will persist over time as demonstrated in Figure 3.

State Versus National Adoption Rates

Recognition of a technology as standard of care can be difficult because there is no universally accepted source that defines standard of care, especially given that clinical context can vary from patient to patient. Furthermore, perceptions of standard of care may vary geographically. Skinner and Straiger (2007), Goodman and Fisher (2015) demonstrate significant variance in physician practice across states. This is due in part due to social and demographic differences by region that impact investment in physical capital and access to specialists. Examples would include robotic assisted procedures, laparoscopic inguinal hernia repairs, single port laparoscopic surgery among others.
Figure 2: Simulated diffusion curves in high and low malpractice climates when probability of a lawsuit depends on adoption rates with state. In this case, ultimate adoption is both incomplete and less than 50%. Perceived benefits are equal in both states; malpractice severity is greater in the blue states.
Figure 3: Simulated diffusion curves in high and low malpractice climates when adoption is state dependent, incomplete but in this case exceeds 50%. Distribution of benefits are equally distributed in both states whereas malpractice severity is greater in the blue states.
Certain states address this through use of a "locality rule". While most states benchmark at the national level, a significant minority (about one-third) have locality rules in place. Locality rules thus emphasize a state level standard of care. In addition to locality rules, there are other reasons to believe that state levels of adoption may be more important than national. When determining the degree to which a technology is employed, physicians may use the practice patterns of network peers as a signal to proxy national rates of adoption. This implies that physicians may be particularly influenced by within-state rates of adoption. We can further extend our model to capture the effects of locality rules or lack thereof by breaking adoption level $a$ into a linear combination of two parts: the state level $a_s$ and the national level $a_n$. Therefore, we have probability of a lawsuit:

$$ p(\alpha a_s + \beta a_n) \text{ with } \alpha + \beta = 1. $$

We then have net costs:

$$ [p(\alpha a_s + \beta a_n) - p(1 - \alpha a_s - \beta a_n)] M_s = C_s $$

As we decrease $\beta$ and increase $\alpha$, state utilization levels are emphasized. Exploring the extreme example where $\beta=0$, we find significant changes to the dynamics of the model. In particular, this allows for variation in both probability of lawsuit $p(a)$ and malpractice severity at the state level. To illustrate the effects of this change, consider the effect of positive information regarding $B_i^t$ received in the first period ($t = 1$) at which point $a_s = a_n = 0$. As above, assume a high and low malpractice state ($M_h$ and $M_l$ respectively). Because adoption levels are equal, the probability of a successful lawsuit, $p(a)$, is equal for both states. As with national benchmarking, $p(0)M_h > p(0)M_l$ and adoption during this period are greater within the low malpractice states than high malpractice states. However, when $t = 2$, decreased relative adoption levels within the high malpractice states imply that physicians face a greater $p(a)$. This discrepancy in lawsuit probability favoring low malpractice states compounds the difference between $M_h$ and $M_l$. Simulations for benchmarking at the state level are demonstrated for two levels of incomplete diffusion - less than 50% (Figure 4) and greater than 50% (Figure 5). Several important differences are seen when these are compared to the simulations using national benchmarking. The long term discrepancy in adoption levels between our two states is exaggerated in the case of diffusion levels less than 50%. Also, should adoption levels greatly exceed 50%, adoption levels cross much later in the diffusion’s time course. State benchmarking exerts its greatest impact in the case when equilibrium benefits of the technology and incumbent practice are similar. This

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6Locality rules date back to 1880s to account for differences between training and resources of rural and urban physicians. Problems with locality restrictions include isolated physicians to become essentially exempt from malpractice, the ability of a few number of physicians to set a low standard of care and difficulty to find expert witnesses from small locals to testify against defendants they may personally know. In addition, with standardized medical education and training as well as improved access to information, physicians should be expected to have similar knowledge bases.

7Even among states that maintain locality rules, specific clauses can vary significantly. The following states are grouped by general approach to locality rule:
State wide standard - Arizona, Virginia, Washington
Same community standard - Idaho, New York
Same or similar community standard - Arkansas, Illinois, Kansas, Maryland, Michigan, Minnesota, Nebraska, North Carolina, North Dakota, Oregon, Tennessee
is illustrated in Figure 6. In this simulation, the mean benefit associated with the technology is 1% greater than that of the incumbent. Increasing its relative benefit to 3% results in a modest 6% increase in equilibrium adoption within the low malpractice state. The same change increases equilibrium adoption rates within the high malpractice states by nearly 60%.
Figure 4: Diffusion curves for new technology within high and low states when malpractice risk is dependent on national rates of uptake. In this case, diffusion rates are modeled at less than 50% resulting in an equilibrium disparity in adoption favoring low malpractice regime.
Figure 5: Diffusion curves for new technology within high and low states when malpractice risk is dependent on national rates of uptake. This curve demonstrates dynamics of diffusion when uptake is incomplete but exceeds 50%. In this case, differences in diffusion are less pronounced with the two curves intersecting closure to the 50% level of adoption.
Figure 6: Diffusion curves for the same technology in states having severe versus moderate malpractice severity when malpractice risk is determined by state rather than national utilization levels. In the first graph, mean perceived benefits of the technology are 1% greater than the incumbent practice. In the second graph, benefits of the technology are 3% greater. The incremental variation in benefits results in a modest increase in equilibrium levels of adoption within the low malpractice states. Increases within high malpractice states are significant.
3.2 Variance in Adoption and Malpractice Pressure

Assume now that physicians make adoption decisions on a patient by patient basis. That is, some patients are ideal candidates for the new technology while others would be considered fringe cases and the physician must choose how aggressive to be with application of the technology. \( t^*_i \) represents the preferred level of technology utilization for agent \( i \) exclusive of malpractice concerns. Define a function \( F(.) \) that represents loss of utility when a different level of adoption \( t_{ij} \) is chosen:

\[
A_{ij} = F_A([t^*_i - t_{ij}]^2)
\]

Therefore

\[
Max\{A_{ij}\} = F(0)
\]

\[
\frac{dA_{ij}}{d[t^*_i - t_{ij}]^2} < 0
\]

Now define a malpractice cost function:

\[
C_{ij} = F_C([t_{ij} - t_j]^2)M_s
\]

Where \( M_s \) is the state specific level of malpractice risk. \( t_j \) represents the average level of utilization for state \( j \); this level is assumed to represent the level of adoption that minimizes malpractice costs. Therefore:

\[
Max\{C_{ij}\} = F(0)
\]

\[
\frac{dC_{ij}}{d[t_{ij} - t_j]^2} > 0
\]

Define the following utility function which the agent maximizes:

\[
U_{ij} = A_{ij} - C_{ij}
\]
Assuming both functions are continuous and non-monotonic, maximization implies:

\[
\frac{dA_{ij}}{dt_{ij}} = \frac{dC_{ij}}{dt_{ij}}
\]

\[
(t^*_j - t_{ij})F_A'(t^*_j - t_{ij})^2 = (t_j - t_{ij})F_C'(t_j - t_{ij})^2M_s
\]

\[
\frac{(t^*_j - t_{ij})F_A'(t^*_j - t_{ij})^2}{(t_j - t_{ij})F_C'(t_j - t_{ij})^2} = M_s
\]

\[
(t_j - t_{ij}) = \frac{(t^*_j - t_{ij})F_A'(t^*_j - t_{ij})^2}{F_C'(t_j - t_{ij})^2M_s}
\]

Differencing with respect to \(M_s\) gives the following:

\[
\frac{d}{dM_s}(t_j - t_{ij}) = \frac{(t^*_j - t_{ij})F_A'(t^*_j - t_{ij})^2}{F_C'(t_j - t_{ij})^2}(-\frac{1}{M_s^2})
\]

Assume that \(t_{ij}^* \neq t_j\). Arbitrarily assume that \(t_{ij}^* > t_j\). This implies that \(t_{ij} < t_{ij}^*\) since both \(C_{ij}\) and \(A_{ij}\) are decreasing along the interval greater than \(t_{ij}^*\). Similarly, \(t_{ij} > t_j\) since both functions are also decreasing along the interval less than \(t_j\). Thus, \(t_{ij} \in (t_j, t_{ij}^*)\). Therefore, at equilibrium, this implies:

\[
\frac{F_A'(t_{ij}^* - t_{ij})^2}{F_C'(t_j - t_{ij})^2} < 0
\]

Define \(D_{ij}\) such that:

\[
D_{ij} = \frac{F_A'(t_{ij}^* - t_{ij})^2}{F_C'(t_j - t_{ij})^2}(-\frac{1}{M_s^2}) > 0
\]

\[
\frac{d}{dM_s}(t_j - t_{ij})^2 = (t_j - t_{ij})(t_{ij}^* - t_{ij})D_{ij}
\]
Since $t_j^* < t_{ij} < t_j$ or $t_j < t_{ij} < t_j^*$ as demonstrated above,

$$(t_j - t_{ij})(t_j^* - t_{ij}) < 0$$

which implies that

$$\frac{d}{dM_s}(t_j - t_{ij})^2 < 0$$

Define interhospital variance $V_{ij}$:

$$V_{ij} = \frac{1}{n} \Sigma (t_j - t_{ij})^2$$

We therefore have that:

$$\frac{dV_{ij}}{dM_s} < 0$$

Thus, we have that increasing malpractice decreases variance in utilization amongst physicians.

4 Empirical Strategy

This paper utilizes three empirical approaches when examining the relationship between malpractice and technological adoption. First, change in adoption with respect to malpractice levels are considered. Next we investigate how malpractice pressure influences the absolute level of adoption. Finally we test for the effect of malpractice pressure on intrahospital variance at the state level.

4.1 Change in Adoption Levels

Classically, the diffusion of most technologies follows a sigmoidal-shaped growth curve. Growth is initially slow. The earliest adopters tend to be innovators themselves or individuals with strong predilection for technology who actively seek out innovation (Rogers 1954). Increasing levels of adoption promote further adoption in a number of ways. First, a growing number of adopters increases the number of communication channels through which non-adopter may become aware of the innovation. Secondly, rising adoption levels also foster an understanding of the technology. Finally, it serves as a signal of quality.
Following period of adoption by innovators and early adoptors, a take-off in adoption occurs. It is during this period that the innovation undergoes significant growth. This corresponds to its uptake by the general population. Once the majority of potential adopters have acted, there typically remains a small residual population of non-adopters. Growth in this final period slows as diffusion approaches its long term equilibrium.

This process highlights the relationship between adoption level and growth. Our model predicts that malpractice pressure will correlate with lower growth rates during the initial period when adoption levels are low. As increasing adoption levels validate the technology, we would expect malpractice to encourage adoption. Thus, growth during this period should correlate positively with malpractice pressure. Our empirical approach begins with dividing begin by dividing adoption levels for each technology into three intervals - early, middle and late $INT_i, i \in \{e, m, l\}$. We then construct the following model controlling for technology, state and year fixed effects ($FE_{mst}$):

$$C_{mst} = \beta_0 + INT_i + \beta_1 MP_{st} + \beta_2 MP_{st} \cdot INT_i + FE_{mst} + \beta_3 X_{i,t} + \epsilon_{i,t}$$  \hspace{1cm} (1)

Where $C_{mst}$ represents the growth in utilization of technology $m$ in state $s$ at time $t$. $X_{st}$ are state level demographic, health and healthcare utilization covariates. $MP_{st}$ is our measure of state and time specific malpractice levels. Our measure of interest is the malpractice/interval interaction term. This term isolates the interval-specific effect of malpractice. Our model predicts that the relationship will be negative in the first period and positive in the second period.

4.2 Adoption Levels vs. Malpractice Pressure

We begin with a linear specification incorporating a threshold effect similar to Card 2008. This approach employs an indicator variable that is positive for observations early in a technology’s process of diffusion - specifically for utilization levels less than $\delta$. Within the interval $(0, \delta)$, the technology is not yet regarded as standard of care. The indicator is interacted with malpractice pressure ($MP_{st}$) to capture the effect of malpractice early in the diffusion process. We therefore expect the coefficient on the interacted term to be inversely related to malpractice since this captures its effect before the technology becomes standard of care. At utilization levels greater than $\delta$, the technology is recognized as standard of care. Within the context of this specification, the indicator disappears, leaving only the malpractice level. Thus, our model predicts that the malpractice coefficient will be positive.

$$S_{st} = \beta_0 + \beta_1 MP_{st} + \beta_2 [S_{st} < \delta] MP_{st} + \beta_3 FE_{mst} + \beta_4 X_{i,t} + \epsilon_{i,t}$$  \hspace{1cm} (2)

The indicator threshold is the level of adoption at which malpractice pressure neither encourages or inhibits further diffusion of the technology. It’s interpretation would therefore be the level at which both clinical options are equally
acceptable practice from a malpractice standpoint. The level at which this occurs is endogenously determined and likely depends on the technology’s various characteristics. Because technologies differ in numerous ways including application, cost, patient population, speed of uptake as well as the ultimate degree of utilization, the point at which malpractice switches from inhibiting to facilitating adoption should vary. Empirically, the threshold is derived as that value that maximizes the $R^2$ when adoption is regressed on malpractice and the indicator. Hansen (2000) demonstrates that derivation of the threshold in this manner produces an unbiased estimate.

Employing this same specification, I test importance of state versus national adoption levels with respect to standard of care using the following approaches:

$$S_{it} = \beta_0 + \beta_1 MP_{it} + \beta_2 [S_{it} < \delta]MP_{i,t} + \beta_3 FE_{mst} + \beta_4 X_{i,t} + \epsilon_{i,t} \quad (3)$$

$$S_{it} = \beta_0 + \beta_1 MP_{it} + \beta_2 [Y_{t} < \delta]MP_{i,t} + \beta_3 + FE_{mst} + \beta_4 X_{i,t} + \epsilon_{i,t} \quad (4)$$

$$S_{it} = \beta_0 + \beta_1 MP_{it} + \beta_2 [S_{it} < \delta]MP_{i,t} + \beta_3 [Y_{t} < \delta]MP_{i,t} + \beta_4 FE_{mst} + \beta_5 X_{i,t} + \epsilon_{i,t} \quad (5)$$

In (3), our empirical specification tests for the effect of state levels of adoption. In addition, a variable for existence of a locality rule is incorporated. Specification (4) includes an indicator for year rather than state level of adoption. Because there exists a single, implicit national level of adoption each year and because the national level of adoption is monotonic with respect to time, we can use year as a proxy for the national level of adoption. Again, a covariate for state level of adoption is incorporated. Finally, in (5), we regress adoption levels on both state and national levels.

### 4.3 Interhospital Standard Deviation and Malpractice

The backbone of our proposed relationship between malpractice and adoption are direct financial incentives that encourage physicians’ practice patterns to resemble those of their colleagues. In addition to its effect on diffusion before and after a technology becomes standard of care, we would expect this mechanism to result in more uniform adoption within states having high malpractice pressure. Specifically, within state interhospital standard deviation in adoption levels should decrease in states with higher malpractice threat. To test this, shares of patients treated with each technology were calculated at the hospital level for each year. Interhospital standard deviation ($V_{it}$) was then calculated for each state-year. I employ the following specification which incorporates technology, state and year fixed effects ($FE_{mst}$):

$$V_{it} = \beta_0 + \beta_1 Malpractice_{it} + U_{it} + FE_{mst} + \beta_4 X_{i,t} + \epsilon_{it} \quad (6)$$
The utilization level of each technology \((U_t)\) is incorporated into the regression to correct for changes in variance associated with the mean level of adoption.

5 Data

5.1 Malpractice Pressure

This paper uses the number of malpractice suits greater than $1 million as a measure of malpractice pressure. The malpractice literature varies significantly in terms of proxies for malpractice pressure. Past literature has utilized tort law reform (Kessler and McClelland 1996), physician perception of liability (Studdert 2005), claims per physician year and average claim value (Jena 2011 and Baldwin 1995), insurance premiums (Yang and Mello, 2009; Baiker and Fischer 2007; Dubay and Kaestner 1999).

There are drawbacks inherent to each of these proxies. Premiums data must be obtained directly from insurance firms. In most regions, there are multiple firms and premiums vary significantly. Studies that have employed premiums typically utilize premium information provided by one insurer. Furthermore, many insurers do not provide coverage nationwide which limits the number of regions that can be analyzed. Furthermore, many hospitals are now providing liability insurance to physicians as part of their compensation package, further obscuring the true cost of insurance. Finally, many insurers have exited the market in many states recently. As the number of insurers decreases, the market may become less competitive with subsequent changes to premiums that reflect market conditions rather than actual malpractice risk.

Physician impression of malpractice pressure is problematic for similar reasons. Any measure in this respect is inherently imprecise due to sampling error. Secondly, there may be bias associated with response rates to such surveys. Finally, this data is typically collected at one point in time. While this method may be appropriate for cross sectional analysis, it does not allow for longitudinal studies.

Malpractice reform has been widely used but because of it’s inherently discrete nature, is not well suited for studying the effect of malpractice over time. Nonetheless, prior research examining at the effect of various malpractice reforms provides valuable insight. Kessler et al. divide reform into two types: direct and indirect. Direct measures include caps and collateral-source offset\(^9\). Indirect measures include reductions in the statutes of limitation, more strict

\(^8\)Interestingly, claims per capita and average claim size do not correlate well - the most stark example being pediatrics which has the second lowest degree of claims per physician but by far the highest average settlement

\(^9\)Malpractice cap reform can be applied in a number of ways. In some cases, only non-economic sources are capped. In others, total liability is capped. Collateral-source offset statutes dictate that the physician is not responsible for costs covered by other sources such as medical bills covered by the patients insurance.
qualifications for expert witnesses, and caps on contingency fees. They find a large and significant decrease in expenditures with respect to direct reform with expenditures actually increasing in the context of indirect reform. The significance of direct reforms, particularly caps, is consistent with those from Danzon (1986) and Sloan (1989) demonstrating that payment caps effected the greatest change in malpractice payouts and insurance premiums.

Given that malpractice caps appear to effect the most change amongst reform types, this paper uses the number of lawsuits exceeding $1 million per physician capita as its measure of malpractice pressure. This number is of particular importance for additional reasons. First, news of large settlements may be more likely to disseminate, making them a potentially important signal to physicians of the malpractice climate. Secondly, the standard medical malpractice policy limits are $1 million dollars per occurrence making lawsuits exceeding this threshold particularly troublesome.

This paper uses malpractice data derived from the National Practitioners Database (NPDB), a clearinghouse maintained by the Department of Health and Human Services for all medical lawsuits within the United States. Submissions to the database are federally mandated, ensuring the comprehensive nature of its data. It includes information for all states for all years since 1986. The database provides the number of lawsuits in each state for each year as well as their size. Per capita measures of each index are derived with data from the Association of American Medical Colleges provides data regarding the number of licensed physicians for each state and year.

5.2 Technologies

Four minimally invasive surgical procedures are employed as technological surrogates: laparoscopic appendectomy, laparoscopic hysterectomy, laparoscopic adhesiolysis and endovascular procedures. In each case, the physician is presented with a binomial choice - the incumbent (“open”) and the technology (“minimally invasive”). Surgical procedures were chosen because malpractice pressure is generally higher for surgeons than for practitioners in other areas of medicine (Jena 2011). Finally, because the minimally invasive approaches demand the surgeons develop a different skill set, the risk of complications is highest following initial adoption (Agresta 2004; Meyers 1996). Data regarding use of each procedure is supplied by the Healthcare Cost and Utilization Project (HCUP), a national database maintained by the Department of Health and Human Services. The dataset provides the number of total procedures - open and minimally invasive approaches - for the period 1997 through 2011 for a total of 15 years. Data is provided for 38 states. However, state participation is not universal for all years. The majority of states began their participation after 1997. In nearly every case, states maintained their database participation following their first year of submissions. In all, there are 395 state-year data points for each of the four technologies.

I define adoption level as the share of each procedure performed using the technology. Figure 2 illustrates the adoption curves for each technology from
1997 to 2011. In each case, there appears to be an early period marked by relatively stable utilization levels followed by a period of more rapid uptake. This is followed by a return to lower levels of change as the technology approaches its equilibrium share. Long run equilibrium rates of technology utilization vary in each case from a minimum of between 30 and 40% in the case of laparoscopic adhesiolysis to greater than 90% for laparoscopic appendectomy.
Covariates including state level income and insurance coverage provided by the US Census. Health and demographic data are drawn from the Behavioral Risk Factor Surveillance System (BRFSS), maintained by the CDC.

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10Demographic covariates include state level education attainment, income, number of men in the household. Health covariates include BMI, perceptions of general and physical health. Health access measures include insurance type, rates at which women receive mammography and hysterectomy rates.
6 Results

6.1 Graphical Overview

Like the diffusion of most technologies, the diffusion of these minimally invasive approaches appear to follow sigmoid-shaped adoption curves. Thus, each technology experiences a period of low growth early in the diffusion process. This is followed by a period of high growth corresponding to the middle portion of the adoption curve before again returning to low growth as the technology approaches its long term saturation point. If high malpractice pressure initially suppresses adoption, we would expect to witness lower growth in these states initially. With further diffusion, the technology becomes standard of care resulting in rapid growth within these states. Conversely, the diffusion within low malpractice states proceeds with little interference which should result in faster growth earlier and lower growth later when compared to their high malpractice counterparts.

We examine the above hypothesis by breaking levels along the adoption curve into three periods - early, middle and late. In this case, adoption levels for each technology were broken into three equal segments. Period specific growth is then averaged across high and low malpractice states. Results are shown in Figure 8.

For all technologies, growth within low malpractice states outpaces growth in high malpractice states while adoption levels are low. When technologies enter the midportion of the adoption curves, characterized by rapid increases in adoption, we find the opposite: growth is highest within those states having the highest malpractice pressure. Consistent with these results, the magnitude of growth averaged across all states falls between high and low pressure states.

While growth rates are useful for getting a sense of how utilization of technology changes over time, they are also subject to limitations. The methods by which data is partitioned into groups will impact the way growth rates are characterized. Secondly, our model makes a stronger assertion than higher growth rates during the period of rapid uptake. While it does inherently predict that malpractice will engender higher growth rates once a technology begins to successfully diffuse, the model goes a step further and predicts that the increased growth will eventually lead to higher total levels of utilization. To this end, we examine levels of utilization for each of the four technologies over time. As above, we consider the characteristics for the ten highest and lowest malpractice states. In this case, adoption levels are averaged across the two groups of states for each year. The results are shown in Figure 9.

As shown, in every case, adoption levels begin lower within the high malpractice states. As suggested by technological growth in Figure 8, adoption within high malpractice states begins to increase more rapidly than low malpractice states. For each technology, adoption within the high malpractice states eventually surpasses those levels within the low malpractice areas. By the end of the sample period, adoption levels are universally greater within high malpractice states.
Figure 8: Growth in the minimally invasive approaches over time. Growth rates conditioned on level of adoption for each of the technologies are averaged across the ten highest and ten lowest malpractice states. In each case, growth within high malpractice states is lower than within high malpractice states when adoption levels are low. Once adoption levels rise, growth rates are highest within states with high malpractice pressure.
Figure 9: Adoption levels of the four minimally invasive technologies over time. Average levels of adoption for the ten highest and lowest malpractice states are shown. For each technology, utilization rates begin at a lower levels in high malpractice climates. Similarly, in each case, mean utilization rates within states having greater malpractice pressure ultimately surpass low malpractice states.
6.2 Pooled Analysis

The graphs above suggest a relationship between malpractice pressure and adoption of medical technology. We formalize hypothesis testing in this section using the empirical models outlined in Section 4, beginning first with changes in adoption level versus malpractice pressure. In the sections following this, the effects of malpractice on absolute adoption levels and interhospital variance are explored. In each case, data from all technologies are pooled.

6.2.1 Change in Adoption vs. Malpractice

I define change in adoption rate as the change in percent of each procedure performed utilizing the minimally invasive technique. Table 1 presents the estimates for a fixed effects regression controlling for each technology, year and state in addition to demographic, public health and personal health controls. Column (1) demonstrates the relationship between change and our three periods. As expected, growth is highly correlated with adoption rates falling within our second period. Estimates from column (2) incorporate state, year and technology fixed effects estimates. In addition, the results from our interactions of interest are shown demonstrating a positive and significant relationship between malpractice and growth in adoption during the second interval, a period that marks the transition of each technology from novel towards standard of care. Column (3) incorporates our covariates without significant change to the estimates or associated standard errors. In each case, standard errors are clustered by state.
Table 1: Change in Adoption Levels Versus Malpractice Pressure

<table>
<thead>
<tr>
<th></th>
<th>Change in Adoption Levels</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Period 2</td>
<td>0.005***</td>
<td>−0.006**</td>
<td>−0.007*</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Period 3</td>
<td>−0.007***</td>
<td>−0.025***</td>
<td>−0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Malpractice</td>
<td></td>
<td>−1.257</td>
<td>−5.489</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.783)</td>
<td>(3.635)</td>
</tr>
<tr>
<td>Malpractice/Period 2</td>
<td></td>
<td>5.688**</td>
<td>7.180**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.784)</td>
<td>(3.602)</td>
</tr>
<tr>
<td>Malpractice/Period 3</td>
<td></td>
<td>4.078</td>
<td>4.767</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.213)</td>
<td>(4.196)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.021***</td>
<td>0.033***</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.005)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Fixed effects?</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Covariates</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,418</td>
<td>1,418</td>
<td>934</td>
</tr>
<tr>
<td>R²</td>
<td>0.031</td>
<td>0.289</td>
<td>0.293</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.030</td>
<td>0.260</td>
<td>0.240</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.027 (df = 1415)</td>
<td>0.024 (df = 1362)</td>
<td>0.024 (df = 868)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>22.860*** (df = 2; 1415)</td>
<td>10.065*** (df = 55; 1362)</td>
<td>5.534*** (df = 65; 868)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
6.2.2 Adoption Levels vs. Malpractice

While change in adoption appears to positively correlate with malpractice pressure as technologies become standard of care, this relationship does not necessitate that growing levels of adoption specifically increase adoption. High malpractice may, for instance, suppress adoption levels throughout the course of diffusion but allow for higher growth during certain periods. Our empirical framework in this section tests for two possible relationships. First, we examine whether increased malpractice pressure results in lower levels of adoption initially. Secondarily, we test whether malpractice risk eventually results in increased adoption levels once the technology becomes standard of care. Similar to the empirical specification for change in adoption rates above, a fixed effects model controlling for year, state and technology is employed. To identify the effect of malpractice, we include a threshold variable representing the adoption level at which the technology becomes standard of care. The threshold variable is interacted with malpractice to give the effect of malpractice during the early stages of adoption. Our model predicts a negative relationship between the interacted variable and levels since this corresponds to the effect of malpractice prior to a technology attaining standard of care. We expect the relationship between the non-interacted malpractice term and adoption to be positive since this corresponds to the effect of malpractice once the technology becomes standard of care. The results are shown in Table 2.

Our results do demonstrate the expected relationship between malpractice and adoption. Column (1) shows the results of our regression in the absence of fixed effects or covariates. While the coefficient for malpractice is positive and that of the interaction term is negative, neither reaches statistical significance. With the addition of state, year and technology fixed effects, we find an 11% reduction in adoption levels for every percent increase in malpractice during the early phases of diffusion. We also find that later in the process of diffusion, once the $\delta$ thresholds have been surpassed, the effect of malpractice on diffusion becomes positive at roughly the same magnitude as shown in column (2). Column (3) demonstrates that these relationships persist with the addition of our demographic and health-related covariates.

Results for our specifications exploring state versus national benchmarking are displayed in Table 3. The first column is similar to our specifications in Table 2 with the addition of a dummy variable for states having locality rules. Similar to our results in Table 2, we find that malpractice exerts a negative effect on adoption early in the course of diffusion while later encouraging adoption. These effects are both statistically significant. While we find similar results when national benchmarking is used, none of these effects reach significance. Our final column employs both state and national benchmarking. We find consistent effects of malpractice on adoption levels; these effects, however, remain significant only for state levels of adoption.
Table 2: Adoption Level Versus Malpractice Pressure

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malpractice</td>
<td>6.732</td>
<td>11.894**</td>
<td>21.574***</td>
</tr>
<tr>
<td></td>
<td>(6.733)</td>
<td>(5.567)</td>
<td>(8.328)</td>
</tr>
<tr>
<td>Malpractice/Low</td>
<td>-0.295</td>
<td>-11.058**</td>
<td>-15.745**</td>
</tr>
<tr>
<td></td>
<td>(8.681)</td>
<td>(5.469)</td>
<td>(7.969)</td>
</tr>
<tr>
<td>Low</td>
<td>-0.354***</td>
<td>-0.182***</td>
<td>-0.171***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.007)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.632****</td>
<td>0.478***</td>
<td>1.004**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.014)</td>
<td>(0.509)</td>
</tr>
</tbody>
</table>

|                       |              |              |              |
| Fixed effects?        | No           | Yes          | Yes          |
| Covariates            | No           | No           | Yes          |
| Observations          | 1,579        | 1,579        | 871          |
| R²                    | 0.773        | 0.920        | 0.922        |
| Adjusted R²           | 0.773        | 0.917        | 0.916        |
| Residual Std. Error   | 0.095 (df = 1575) | 0.057 (df = 1525) | 0.057 (df = 804) |
| F Statistic           | 1,789.151*** (df = 3, 1575) | 323.441*** (df = 54, 1524) | 144.840*** (df = 66, 804) |

*Note:* *p<0.1; **p<0.05; ***p<0.01
Table 3: Adoption Level Versus Malpractice Pressure: State vs. National Benchmarking

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Malpractice</td>
<td>22.285***</td>
<td>4.889</td>
<td>23.828***</td>
</tr>
<tr>
<td></td>
<td>(8.233)</td>
<td>(8.379)</td>
<td>(8.529)</td>
</tr>
<tr>
<td>Early State Level Adoption</td>
<td>−0.171***</td>
<td>−0.138***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Malpractice/State Level Adoption</td>
<td>−16.111**</td>
<td>−20.684***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(7.940)</td>
<td>(7.580)</td>
<td></td>
</tr>
<tr>
<td>Early National Adoption Level</td>
<td></td>
<td>0.185***</td>
<td>0.088****</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Malpractice/Early National Adoption Level</td>
<td>−8.516</td>
<td>0.356</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(8.889)</td>
<td>(7.059)</td>
</tr>
<tr>
<td>Locality Laws</td>
<td>0.005</td>
<td>0.018</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.042)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Constant</td>
<td>1.001**</td>
<td>0.369</td>
<td>0.815*</td>
</tr>
<tr>
<td></td>
<td>(0.506)</td>
<td>(0.607)</td>
<td>(0.482)</td>
</tr>
</tbody>
</table>

Fixed effects? Yes Yes Yes
Covariates Yes Yes Yes
Observations 871 871 871
R² 0.922 0.888 0.930
Adjusted R² 0.916 0.879 0.924
Residual Std. Error 0.057 (df = 805) 0.069 (df = 805) 0.054 (df = 803)
F Statistic 147.186*** (df = 65; 805) 98.209*** (df = 65; 805) 158.968*** (df = 67; 803)

Note: *p<0.1; **p<0.05; ***p<0.01
6.2.3 Variance and Malpractice Pressure

Thusfar, our results appear to be consistent with a mechanism by which malpractice inhibits early diffusion before encouraging it once a technology becomes standard of care. In this context, malpractice punishes physicians should they stray from the herd. If valid, this mechanism should have other consequences. As predicted by our model in Section 3.2, we would expect to see less variation between hospitals in their utilization of technologies within high malpractice states. I employ this prediction as a robustness check. Results from our third specification are presented in Table 3. Our dependent variable in this case is standard deviation of interhospital levels of technology utilization. Because there is significant variation in the number of procedures that each hospital performs, hospitals are weighted in proportion to the total number of procedures (minimally invasive and open) they perform. The first column shows the results of regressing our weighted standard deviation on adoption level. The relationship is negative but non-significant. The relationship persists with the addition of fixed effects. With the addition of covariates, we find that a 1% increase in malpractice pressure translates to a 12% decrease in interhospital standard deviation. This relationship is significant.
<table>
<thead>
<tr>
<th></th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Malpractice</td>
<td>−0.248</td>
</tr>
<tr>
<td></td>
<td>(3.022)</td>
</tr>
<tr>
<td>Adoption Level</td>
<td>0.024***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.173***</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
</tr>
<tr>
<td>Fixed effects?</td>
<td>No</td>
</tr>
<tr>
<td>Covariates</td>
<td>No</td>
</tr>
<tr>
<td>Observations</td>
<td>1,538</td>
</tr>
<tr>
<td>R²</td>
<td>0.005</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.004</td>
</tr>
<tr>
<td>Residual Std. Error</td>
<td>0.066 (df = 1535)</td>
</tr>
<tr>
<td>F Statistic</td>
<td>4.171** (df = 2; 1535)</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01
7 Conclusions and Policy Implications

The threat of litigation incentivizes physicians to act similarly. In the context of new medical technologies, this means that higher levels of malpractice inhibit diffusion initially before a breakpoint is reached at which time the technology becomes standard of care. From this point forward, malpractice encourages physicians to adopt. We demonstrate evidence for this relationship in a number of ways. First, we find that within high malpractice states, growth rates begin lower during the early phase of diffusion. Later in the diffusion process, growth within high malpractice states overtakes those having low malpractice pressure. We then examine how malpractice impacts adoption levels over time. Similar to growth rates, we find that higher malpractice leads to lower adoption levels initially. With further diffusion, malpractice eventually leads to higher rates of adoption. Finally, as a robustness check, we consider the effect of malpractice on variation in uptake within states. We find that high malpractice does appear to be correlated with decreased variance in uptake between hospitals.

These findings suggest a number of possible policy and clinical implications. The clinical relevance of malpractice pressure has only been considered in the context of defensive medicine. The results from this paper suggest that malpractice may, in some capacity, help to vet new technologies by encouraging restraint early in the diffusion process. It may be during a technology’s infancy that dangers and other pitfalls are discovered and thus patients are somewhat shielded from these risks. Simultaneously, once a technology has demonstrated itself to be safe and widely applied, its diffusion is enhanced. These characteristics apply not just to the clinical aspects of medical technology but their costs as well - malpractice inhibits the use of unproven technology. This stands in stark contrast to the practice of defensive medicine which is widely thought to increase spending.

This information may be of particular use to pharmaceutical companies when making product marketing decisions. Specifically, resources allocated to promoting the product in low malpractice states may have two benefits: the direct benefits of marketing as well as the effects vis-a-vis the social multiplier by virtue of raising adoption levels.

The relationship between malpractice and adoption may have empirical significance as well. If we assume that malpractice statutes are unrelated to a population’s health status, we have the potential to use malpractice pressure as an instrumental variable. In order to satisfy the monotonicity prerequisite, malpractice could only be applied as an instrument early in a product’s diffusion. This restriction is not important in a practical sense, however, because it is during the early phase of diffusion that the least amount of evidence is available. Certain medical advances, such as pharmaceuticals require FDA approval which is typically predicated on positive results from randomized experiments. A significant number of medical advances, however, have not been evaluated this rigorously. Examples include many new devices, surgical procedures, treatment algorithms, off label use of pharmaceuticals, among others. Much of the evaluation of such technologies comes in the form of retrospective analysis which are subject to multiple sources of bias. If successful, this application could minimize
the bias inherent to these studies, thereby providing more reliable insight into their value to patient health.

Finally, these results may provide a quantitative means of declaring a technology standard of care. In some cases, this may be obvious, such as instances where the technology reaches near complete saturation. For example, once the technology is applied in the majority of cases, one might reasonably defend its use as standard of care. Many technologies, however, do not attain 100% penetration. Instead, many innovations are reserved for certain clinical scenarios, such as the case of laparoscopic adhesiolysis. Defending a technology as standard of care may be difficult if it is only employed in 20% of cases. However, because physicians recognize the indications for certain technologies, the effect of malpractice should hold even if the long term equilibrium rate of utilization is low.
8 References


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