When IT Creates Legal Vulnerability: Not Just Overutilization but Underprovisioning of Health Care Could be a Consequence

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We study the potential impact of the legal vulnerability created by ubiquitous information technology (IT) and provide insights into its unintended consequences in a typical healthcare context. Informed by algorithmic predictions based on risk information, screening policies determine the level of care provision (i.e., whether to conduct a test). When such predictions are provided to physicians via IT in the testing stage, follow-up decisions could be more accurate. Yet, physicians may also observe heightened legal risk due to increased information visibility. In this context, we examine the socially optimal screening (based on risk information) and follow-up policies (based on risk and test information) in light of increased visibility of patient data due to health IT and possible litigation risks associated with it. We find that strategic underprovisioning of health care, therefore a lower utilization of health care services, through screening policies could potentially mitigate the adverse impact of health IT. The underprovisioning of health care is aggravated if the precision of the risk factors relative to that of the medical test increases or the physician becomes more self-interested and less patient-oriented. On the other hand, limits on malpractice damage can alleviate the underprovisioning of health care.

Key words: health IT, algorithmic decision making, medical litigation, information sharing, game theory

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1. Introduction

Although information technology (IT) offers numerous opportunities to create social and economic value, ubiquitous IT may create new vulnerabilities. Motivated by this observation, Ransbotham et al. (2016) identify several mechanisms through which such vulnerabilities are created and outline a research agenda for exploring the societal problems resulting from IT. One of those mechanisms is the increased visibility of information. The IT-induced information visibility, while offering several benefits such as increased transparency and better decision making, can also enable or exacerbate privacy concerns and intellectual property theft. Another significant downside to the enhanced
information visibility is the increased legal vulnerability decision makers face in the event of an adverse outcome, which is the focus of this paper.

One of the legal implications of wider use of IT is that it enables plaintiffs to have easier access to evidence data in support of a lawsuit. In particular, when decision makers choose actions based on a multitude of information, IT facilitates the plaintiffs to discover and exploit information that favors their case. For a specific example in healthcare, consider the malpractice lawsuits against radiologists. One of the most cited bases for lawsuits is the failure to diagnose breast cancer when physical breast examination indicated a palpable mass—an indicator of a breast lesion—even though the subsequent mammogram result does not warrant a cancer diagnosis (Brenner 2004). In these cases, it is often argued, and sometimes successfully, that the radiologist did not give adequate weight to individualized patient risk based on clinical history while interpreting the mammogram and providing the recommendation. Consistently, it is recognized that widespread adoption of electronic health records (EHRs) and health information exchanges (HIEs) heightens health care providers’ duties to search for patient information generated by IT (such as the physical examination results and other risk factors indicating the risk of developing the disease presented to the radiologist in the form of an algorithmic prediction) and creates a legal responsibility to act on that information (Mangalmurti et al. 2010). The phenomenon—the heightened legal vulnerability faced by decision makers because of IT (or associated increased information visibility)—arises in many other contexts including security, crime prevention, and law enforcement (e.g. see, Pena 2008, O’Neill 2005, Madigan 2018).

A significant consequence of increased litigation risk is that the decision makers resort to defensive actions which are solely undertaken to diminish the legal liability. Such defensive actions are generally wasteful to the society. For instance, in the health care context, physicians’ provision of unnecessary care due to fear of being sued is known as defensive medicine (Kessler and McClellan 1996). More than 80% of physicians report practicing defensive medicine (Hermer and Brody 2010), which leads to an estimated wasteful spending of $45 billion nationwide annually (Chandra et al. 2012). Therefore, from a social planner’s perspective, designing a system or a set of policies that accounts for the decision makers’ response to the possible increased litigation risk created by IT is critical. Towards this end, we examine the social planner’s problem using health care as an illustrative context.

1.1. Legal Vulnerability from Health Care IT

Since the passage of Health Information Technology for Economic and Clinical Health (HITECH) Act, the U.S. government has been promoting the widespread adoption of EHRs and health information sharing among providers through HIEs. As of 2015, almost all the hospitals have adopted basic EHRs, and nearly three-quarters of hospitals have adopted HIEs (The Office of the National Coordinator for Health Information Technology (ONC) 2016). Many studies have shown

Among the various adverse effects of health IT, increased physician vulnerability to malpractice litigation has been widely discussed (Ozeran and Anderson 2011, Sittig and Singh 2011). In an influential article published in the New England Journal of Medicine, Mangalmurti et al. (2010) identify the effects of health IT on three key areas of medical malpractice litigation: (i) care process and litigation risks, (ii) litigation process, and (iii) standard of care. First, health IT amplifies the health care providers’ legal responsibility to act on vast amounts of information regarding a patient’s health condition (Benbassat et al. 2001, Carney et al. 2012). Second, more extensive documentation of clinical activity throughout the health care system creates more discoverable evidence for plaintiffs in the lawsuit and the mining of the metadata from the patient EHRs can make it easier to find evidence for physician’s sub-optimal decision making (Ozeran and Anderson 2011, Ransbotham et al. 2015). Third, as evidence-based clinical decision support systems (DSS) get embedded in health IT systems, courts could increasingly rely upon the clinical guidelines and policies embedded in such systems for judging the merits of a lawsuit (Brown and Miller 2011).

1.2. Research Questions and Contributions

In this paper, we examine the potential impact of the legal vulnerability created by ubiquitous IT and provide insights into its unintended consequences. Clearly, a social planner, such as the Centers for Medicare and Medicaid Services (CMS) or the professional medical societies, would formulate policies that seek to maximize the social payoff while accounting for how health care providers will respond to the increased visibility of patient data and possible litigation risks associated with it. Taking the social planner’s perspective, we seek to answer the following key research questions:

(R1) Can the social planner develop policies that will induce the first-best solution that maximizes social welfare in the presence of litigation risk and health IT?

(R2) When the policies do not achieve the first-best, what are the adverse impacts of information sharing enabled by health IT?

(R3) How can the adverse impact be mitigated?

To study the social impact of legal vulnerability created by IT, we develop a stylized game-theoretical model of a health care context as in the following. A physician conducts a medical test
on a patient that visits him and then recommends a follow-up (which could be a treatment or further testing), or no further action. The medical test and any subsequent follow-up are typically not needed by all patients and, may sometimes incur unnecessary costs, and to some patients, even do more harm than providing benefits. A social planner develops screening policies that specify who should see the physician based on specific indicators such as the existence of certain risk factors and/or clinical history\(^1\), and, follow-up policies that specify the recommended course of action based on test results and/or risk factors. We refer to the patient information (e.g. prior medical history, family history, etc.) used for screening patients as risk information and the information collected from the medical test results as test information.

Because information visibility is a key determinant of legal liability, we focus on the information sharing role of health IT. In the presence of health IT, both the risk and the test information are available to the physician at the time of decision making. Yet, in the absence of health IT, the risk information may not be readily available to him. Indeed, health IT is the primary source for physicians’ access to risk information in diagnostic decision making. For example, in the case of a radiologist interpreting an image, he may or may not have access to the risk information (Carney et al. 2012, Lin et al. 2010). Radiologists typically do not interact with patients, and hence, cannot obtain such information from them during a medical encounter. Instead, radiologists mostly rely on radiology information systems (RIS) or EHRs to access such information, should they seek to use it in their decision making (Lin et al. 2010). Availability of information via RIS or EHRs not only ascertain the presence of pertinent clinical risk information to radiologists, but also, it can systematize such information into algorithmic predictions as part of clinical decision support (Nance Jr et al. 2013). Hence, health IT has a core role in sharing of information, possibly through algorithmic predictions in the form decision support systems, which relates to legal liability emanating from its visibility.

Consistent with empirical observations (e.g., see Studdert et al. 2005), the patient files a lawsuit against the physician in the case of a false-negative outcome. The success of the lawsuit (i.e., whether the patient wins the lawsuit) depends on the availability of information (i.e., the clinical risk information in the form of an algorithmic prediction) to the physician at the time of decision making and the screening and follow-up policies regarding the usage of such information. While the social planner seeks to maximize the social welfare, the physician considers his own payoff and possibly that of the patient as well while choosing his recommendation. Therefore, the social planner’s and the physician’s incentives to provide health care are not necessarily aligned.\(^2\)

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\(^1\)Some examples are the demographics and risk factors-based cancer screening policies issued by major cancer organizations such as the American Cancer Society (ACS) or the U. S. Preventive Services Task Force (USPSTF), which recommend that women at a higher risk of developing cancer should initiate cancer screening at an earlier age, compared with their peers. For estimating risk, many validated risk calculators exist for various types of cancers.

\(^2\)We remark that numerous medical contexts fit the above setup. Examples include, but are not limited to, a cardiologist deciding a course of action based on EKG test results and risk predictions based on patient’s clinical history (Mackey
We make several key contributions to the literature and provide important policy implications. The main findings are as follows.

(i) When malpractice litigation is not a concern for the physician or when the patient’s risk information is not shared with the physician, the social planner can set policies that induce the first-best solution. On the other hand, when litigation is a concern and the risk information is shared with the physician, the social planner is unable to always induce the first-best solution. This finding demonstrates that the legal vulnerability created by IT can be harmful to the society.

(ii) The legal vulnerability created by health IT is the result of potential conflicts between the risk information and the test information. When such conflicts increase the likelihood of the patient winning the lawsuit, the social planner is unable to induce the first-best solution. This finding identifies one specific mechanism, i.e. information conflict, by which information visibility creates legal vulnerability.

(iii) When the benefit of follow-up is sufficiently large, even when information sharing creates a legal vulnerability, the social planner sets the same screening and follow-up policies as in the first-best solution but the physician behaves more defensively under information sharing than under no information sharing. That is, the heightened legal vulnerability created by health IT leads to the predictable defensive behavior by physicians. This finding is consistent with the well-documented prevalence of overutilization phenomenon, i.e. physicians provide more care due to litigation concerns while there is no medical indication to do so (Cassel and Guest 2012).

(iv) When the benefit of follow-up is moderate, underprovisioning of health care for high-risk patients can be the socially optimal strategy in the presence of information sharing. For instance, a high-risk patient is sometimes not recommended testing in the presence of information sharing whereas she would be recommended testing in the absence of it. This finding stands in sharp contrast to conventional wisdom that legal vulnerability results in overutilization of health care. On the other hand, this finding provides theoretical support to the arguments of some that underprovisioning may be necessary to curtail the overutilization of health care (Grady and Redberg 2010, Schwartz et al. 2014).

(v) An increase in the precision of risk information relative to that of the test information intensifies the need for socially optimal policies requiring underprovisioning. This somewhat surprising result suggests that as the availability of vast amounts of population health data increases the predictive power of patient risk models, such an increase may lead to policies that promote underprovisioning to mitigate physicians’ legal concerns. On the one hand, sharing the more precise risk information will improve physician decisions (Aron et al. 2011). On the
other hand, more precise risk information can exacerbate the need for policies that indicate underprovisioning of health care because of litigation concerns. A more self-oriented physician also leads to a similar impact.

(vi) Although underprovisioning of health care through screening policies could potentially mitigate the adverse impact of health IT, we find that imposing malpractice damage caps in addition to setting optimal policies can be useful in reducing, but not completely eliminating, the need for underprovisioning.

2. Related Literature
This paper primarily relates to research on health IT and health care economics. Interest in the value of health IT has surged in the last decade (Menon et al. 2000, Aron et al. 2011, Chaudhry et al. 2006, Walker et al. 2005, Ayal and Seidman 2009, Menon and Kohli 2013, Vest and Gamm 2010, Bhargava and Mishra 2014). An early study by Menon et al. (2000) provided empirical evidence that IT contributes positively to the production of health services at the industry level. Aron et al. (2011) showed that the use of information systems by trained health care professionals reduces medical errors at the hospital level. Bhargava and Mishra (2014) studied the impact of EHRs on an individual physician’s performance and found that the long-term benefits from EHRs depend on the physician specialty. Chaudhry et al. (2006) found that the quality improvement effect of health IT is particularly significant in preventive care. Menon and Kohli (2013) showed that improved quality through health IT could contribute to lower malpractice insurance premium. Recognizing the importance of coordination across care providers, the focus of health IT research has recently shifted to interoperability between health IT systems (Vest and Gamm 2010). Walker et al. (2005) estimated $78 billion would be saved by integrating fragmented health data via HIEs. Ayal and Seidman (2009) quantified the benefits of integrating information systems in hospitals.

Although the benefits of health IT in terms of improving various performance metrics have been widely documented, academic research on potential drawbacks of health IT is limited (Agarwal et al. 2010). As the implementation of digitized health records expands, physicians are increasingly exposed to the risk of data breach (Garfinkel et al. 2007). Also, the large volume of data included in a health record forces physicians to spend more time on reviewing a patient’s health (Singh et al. 2013) and, some have suggested, that it would make it more difficult for physicians to identify key information (Ozeran and Anderson 2011). It was pointed out that such consequences not only delay physicians’ decision process but also jeopardize patient safety (Beasley et al. 2011). We contribute to the literature on potential drawbacks of health IT in relation to its impact on the malpractice environment via economic modeling to capture the trade-offs and derive implications. Previous research related to our work was mostly qualitative and has articulated the health IT and
malpractice connection using case studies and anecdotal examples. The main message from this stream of research is that the adoption of health IT will increase a physician’s liability (Singh et al. 2013, Mangalmurti et al. 2010, Beasley et al. 2011, Ozeran and Anderson 2011, Garfinkel et al. 2007). A recent empirical study provided some evidence for increased liability in the case of basic EHR use when risk is measured in dollar value of paid claims, yet found that the direction of impact could change in the case of advanced EHR use (Ransbotham et al. 2015).

In recent years, there has also been a growing interest in health IT research using analytical models. The focus within this stream has been on financial incentives for health IT adoption (Demirezen et al. 2016, Ozdemir et al. 2011) or the incentive misalignment among health care providers in sharing and securing health information (Huang et al. 2014, Bai et al. 2014). In this study, we extend the growing body of research on health IT by examining the role of health IT in physicians’ litigation concern and the resulting defensive medicine using an analytical model.

In health care economics, our research is related to policies regarding health care provision. It is standard practice to code various policies, including the use of health information, in the form of guidelines (Rosenfeld et al. 2013). While scientific evidence and body of knowledge is the predominant factor that guides the development of guidelines, the health care literature has also documented economic and legal factors that are considered by policy makers (Rosenfeld et al. 2013). For instance, though guidelines are not legally enforced on physicians, they are often considered in defining physicians’ responsibility and legal standards of care in a medical lawsuit (Samanta et al. 2006, Mello 2001). The necessity of using health care guidelines in defining legal standards has attracted more attention in recent years (Blumstein 2006, Bovbjerg and Berenson 2012, Orszag 2010). However, there is conflicting evidence regarding the effect of guidelines on determining legal standards of care (Mackey and Liang 2011, Woolf 1998, The Office of Technology Assessment (OTA) 1994, Mello 2001). Our research contributes to this discussion by demonstrating that the litigation risk introduced by the increased data sharing may give rise to policies that lead to underprovisioning relative to that suggested by scientific body of knowledge.

On the modeling side, our paper is related to the gatekeeper models that have been studied in the operations management and airline/information security literatures (Cavusoglu et al. 2010, 2013, Ulvila and Gaffney Jr 2004, Ryu and Rhee 2008). The seminal research by Shumsky and Pinker (2003) considered a two-staged service model where gatekeepers provide an initial service to customers and refer some customers to a specialist in a principal-agent problem context. The model was extended to stochastic environments, outsourcing, and security contexts respectively by Hasija et al. (2005), Lee et al. (2012), and Zhang et al. (2011). Freeman et al. (2016) empirically examined the association between system congestion and gatekeeping behavior in a health care setting. Recently, Adida and Bravo (2017) studied how a payer can incentivize a primary caregiver (the
gatekeeper) and a provider (specialty care) to coordinate their efforts via optimal design of contracts. The major difference in our model is that a social planner serves as the gatekeeper in the first stage whose incentives may conflict with those of the specialist in the second stage. Furthermore, the prior literature on gate keeper models does not focus on the litigation concerns as this paper does.

3. Model Setup

Our model is similar to the gatekeeper models widely used in the health care operations literature. The health care service setup consists of two types of patients based on their health status. The patient’s true health status $i$ is unhealthy ($u$) with probability $\lambda$ and healthy ($h$) with probability $1 - \lambda$. Two types of information, the risk information and the test information, are relevant for making a determination about the patient’s health status. The risk information is used for making the recommendation to take the test (e.g., recommend bowel cancer test for patients with strong family history, where family history status captures the risk information.) After the test is performed, the physician uses the test information and the risk information, if available to him, to decide whether to recommend a follow-up or not. Each information source provides a binary signal, high ($H$) or low ($L$), about the patient’s true health status $i \in \{h,u\}$. We use $s_r$ to denote the signal from the risk information and $s_t$ to denote the signal from the test information. We use discrete signals in our model because even when signals are continuous, decisions are often made after converting them into discrete quantities in practice. For instance, in the case of breast cancer risk assessment based on mammography, radiologists report one of the six BI-RADS categories to represent the likelihood of malignancy (Eberl et al. 2006). As in almost all medical tests, signals are informative but noisy, where the precision of a signal is measured by sensitivity (true-positive rate) and specificity (true-negative rate) (Zweig and Campbell 1993). Sensitivity and specificity of $s_r$ ($s_t$) are denoted by $r_u$ ($t_u$) and $1 - r_h$ ($1 - t_h$), respectively, where $r_u > r_h$ and $t_u > t_h$ (i.e., true positive rate is greater than the false positive rate). The signal from the test is more informative about the patient’s health status than the signal from risk information, and therefore $t_u > r_u$ and $t_h < r_h$. Following the classification literature (Cook et al. 2000, Han et al. 2011, p. 315), we assume that the two signals are conditionally independent given a patient’s health status. Although the relaxation of this assumption does not change our results qualitatively, it would make our modeling and analysis more complex.

In the main model, we assume the risk information is shared with the physician. We depict the sequence of events under the main model in Figure 1. In Stage I, the social planner decides two sets of health care policies: (i) screening policies regarding which patient should be tested based on risk information (e.g., screen for bowel cancer if a family history is present), and (ii) follow-up policies regarding whether the physician should recommend a follow-up or not based on the test information and the risk information (e.g., conduct a biopsy if either the family history is strong or if the family
history is weak but the test result is positive). If recommended by the screening policy, the patient visits the physician for the test. In Stage II, the physician performs the test and makes a follow-up recommendation based on the test information and the risk information. In Stage III, the true health status of the patient is realized. In case of a false-negative recommendation by the physician, i.e., if the physician does not recommend a follow-up for an unhealthy patient, in Stage IV, the patient files a lawsuit against the physician\(^3\) and the court provides a judgment on the lawsuit. Finally, in Stage V, the utilities for all players are realized. Table 7 in the appendix summarizes the notation used in our model, further details of which are presented in the following subsections.

Figure 1  Timing of the game

Notes. In Section 4, we introduce four different scenarios (first-best, no-litigation, no information sharing, and information sharing under litigation). If the litigation is not a concern (first-best and no-litigation scenario), Stage IV doesn’t exist.

3.1. Decision Variables

In Stage I of the game, the social planner chooses \(\theta_{sr}\) and \(\phi_{sr, st}\), respectively denoting screening and follow-up policies, to maximize expected social utility. \(\theta_{sr}\) denotes the probability that a patient with risk signal \(s_r\) should undergo the testing, and \(\phi_{sr, st}\) denotes the probability that a patient with individual risk signal \(s_r\) and test signal \(s_t\) should be recommended a follow-up action.

In Stage II, we denote the physician’s follow-up decision as \(\eta_{sr, st}\) which represents the probability that a follow-up is recommended. Note that the physician could deviate from the social planner’s follow-up policy, hence the value of \(\eta_{sr, st}\) may be different from that of \(\phi_{sr, st}\).

\(^3\) A more general model in which only a fraction of patients with a false-negative outcome files a lawsuit yields qualitatively similar results to those presented in this paper. The assumption that a lawsuit is filed only when there is a false-negative recommendation is consistent with the empirical observations (Studdert et al. 2005).
3.2. Utilities

The utilities for the patient, physician, and the social planner depend on the outcome realized at the end of Stage I for a patient that does not visit the physician and at the end of Stage V for a patient that visits the physician. The possible outcomes are depicted in Figure 7 in the Appendix. We denote the patient’s utility as $U^{PA}$ which is composed of benefits (in life years) and costs (in dollars). We convert all the benefits and costs into the same utility unit using willingness-to-pay ratio, which assigns a cost the society is willing to pay for one year increase in life and is well-established in the health economics literature (Drummond et al. 2015). If the outcome is true-negative (TN), the patient receives $v$ as the base utility representing the reassurance of the absence of the disease. Without loss of generality, we normalize $v$ to zero in our analysis. The cost (or (dis)utility) of test for the patient is $c_t$, which includes costs associated with taking the test and the consultation of the physician in Stage II. If the outcome is false-negative (FN), the patient incurs an additional (dis)utility of $d$, which excludes the utility related to litigation (please also see the next paragraph for more on this). For a true-positive (TP) outcome, the patient (dis)utility decreases to $d(1-\mu)$ (i.e., $0 < d(1-\mu) < d$), where $\mu < 1$ is the percentage reduction in loss due to follow-up. Finally, the patient with a false-positive (FP) outcome receives a utility of $v - c_{FP}$ where $c_{FP}$ refers to the (dis)utility or inconvenience associated with a false-positive outcome.

Recall that a litigation event occurs in the case of a FN outcome. Without loss of generality, we normalize the patient’s litigation-related cost to zero and assume that the patient receives a compensation of $k$ from the physician if she wins the lawsuit. The outcome of the lawsuit is uncertain not only because of uncertainty associated with risk and test information in predicting the health status and that with medical knowledge, but also because of variability associated with judges’ interpretation of the health care policies regarding the right course of action. Since health care policies play a critical role in judges’ evaluation of the merits of the lawsuit (Renshaw et al. 2014), the probability of the patient winning the lawsuit is a function of the social planner’s policies. In practice, the patient usually has a higher likelihood of winning the lawsuit if either the screening policy or the follow-up policy strongly recommends (i.e., recommend with a higher probability) that a patient be tested or followed up. Thus, the probability of the patient winning the lawsuit is monotonically increasing in $\phi_{srs_t}$ and $\theta_{sr}$. We define the probability of the patient winning the lawsuit for a given pair of $s_r,s_t \in \{H,L\}$ as $f(\theta_{sr},\phi_{srs_t}) = a_{srs_t}\theta_{sr} + b_{srs_t}\phi_{srs_t}$, where $a_{srs_t}$ and $b_{srs_t}$ are non-negative constants such that $a_{srs_t} + b_{srs_t} \leq 1$. We normalize $f(\theta_{sr},\phi_{srs_t})$ to zero if the two signals are both low (i.e., $s_r = s_t = L$), which implies that neither of the two signals provides support to the patient’s claim.\footnote{Assigning a positive probability of litigation success for the patient even when both signals are low has the sole effect of expanding the parameter space where the physician will practice defensive medicine in equilibrium under every case we examine.}

The physician is concerned about the patient’s welfare as well as his own payoff. Therefore, the physician maximizes the total utility, $U^{PH}$, which is composed of two parts: the patient’s utility
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(U\textsuperscript{PA}) and her own utility (U\textsubscript{O}\textsuperscript{PH}). The physician’s own utility is composed of the litigation related cost and a fixed amount of payment received from the patient for conducting the test and providing a recommendation. We let U\textsuperscript{PH} be such that U\textsuperscript{PH} = \alpha U\textsuperscript{PA} + (1-\alpha) U\textsubscript{O}\textsuperscript{PH} where \alpha is a weight assigned by the physician on the patient’s utility and captures the physician’s benevolence to the patient in her objective (Godager et al. 2015, Clemens and Gottlieb 2014). To rule out the unrealistic scenario where the physician receives a higher utility when he loses the litigation than when he wins, we restrict the weight on patient’s utility \alpha < 0.5. The physician receives a payment of u from the patient for providing care to the patient, which is a fraction of the patient’s cost of testing c. Furthermore, if there is litigation, the physician incurs a legal cost of l, and in case the patient wins the lawsuit, an additional cost of k which is the compensation provided to the patient. For the social planner, the total welfare is defined as the sum of the patient’s utility U\textsuperscript{PA} and the physician’s own utility U\textsubscript{O}\textsuperscript{PH}. Table 1 summarizes the above discussion on the utilities for the patient, the physician, and the social planner.

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<tr>
<th>Utilities</th>
<th>Decision Outcomes</th>
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<td>Screening</td>
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<td>TN</td>
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<tr>
<td>U\textsuperscript{PA}</td>
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<tr>
<td>U\textsuperscript{PH}</td>
<td>N/A</td>
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<tr>
<td>U\textsubscript{SP}</td>
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Notes. SP: social planner, PH: physician, PA: patient. We use “N/A” to denote the case when no utility is applicable.

Using the utility parameters discussed above and the likelihood of different outcome scenarios, we can compute the expected utilities for the patient, the physician, and the social planner (see Equations (5)-(14) in the Appendix). We breach the notation and denote the parameterized forms of U\textsubscript{SP} as U\textsubscript{SP}(...), U\textsuperscript{PH} as U\textsuperscript{PH}(...), and U\textsuperscript{PA} as

\[ U\textsuperscript{PA}(\eta_{\text{st}}, s_t, \theta_{\text{st}}, \phi_{\text{st}}, \phi_{\text{st}}) \]

Then, the social planner’s problem in Stage I is formulated as below.
Maximize
\[ \theta_{sr,\phi_{sr,s_t}} \forall s_r \in \{H,L\}, s_t \in \{H,L\} \]
subject to
\[ 0 \leq \theta_{sr} \leq 1, \forall s_r \in \{H,L\}, \]
\[ 0 \leq \phi_{sr,s_t} \leq 1, \forall s_r \in \{H,L\}, \forall s_t \in \{H,L\}. \]

In Stage II, we formulate the physician’s problem as below, and solve it separately for each combination of \( s_r \in \{H,L\} \) and \( s_t \in \{H,L\}. \)

\[ \text{Maximize} \]
\[ E[U^{SP}(\theta_H, \theta_L, \phi_{HH}, \phi_{HL}, \phi_{HL}, \phi_{LL})] \]
\[ \text{subject to} \]
\[ 0 \leq \theta_{sr} \leq 1, \forall s_r \in \{H,L\}, \]
\[ 0 \leq \phi_{sr,s_t} \leq 1, \forall s_r \in \{H,L\}, \forall s_t \in \{H,L\}. \]

4. Model Analysis

We examine four cases in order to isolate the impacts of the heightened litigation vulnerability created by information sharing. First, we examine the global optimal case where all decisions are made by a centralized social planner and there is no litigation concern. Thus, in this case, Stage IV does not exist in the game sequence discussed in the model section and the social planner makes decisions in both Stage I and Stage II. This case is the benchmark because the solution offers the best possible or maximum social utility for any given set of model parameters. We refer to this scenario as the first-best (Section 4.1). The other three cases model the decentralized setup in which the social planner sets up screening and follow-up policies, and the physician makes decisions regarding follow-up by maximizing his own expected utility. In the second case, the risk information is shared with the physician but litigation is not a concern for the physician. We refer to it as the no litigation case (Section 4.2). Third, we analyze the case where the litigation is a concern, but the risk information is not shared with the physician. We refer to it as the no information sharing case (Section 4.3). Finally, we consider the case that incorporates the physician’s litigation concern and information sharing and refer to it as litigation and information sharing case (Section 4.4).

The comparison between the first-best and the other cases provides insights into the impact of the decentralized setup under various conditions, i.e., how the differing incentives of the social planner and the physician affect the social planner’s policies and the social welfare, and the role of litigation and information sharing. In all cases, we assume that when the social planner is indifferent between two policies and if one of them is identical to that under the first-best, then he will choose the one that is identical to the first-best to break the tie. Also, if the physician is indifferent between practicing and not practicing defensive medicine, then the physician will choose not practicing defensive medicine.
4.1. First-best Case

In the first-best case, the social planner chooses $\theta_{s_t}$ and $\phi_{s_r,s_t}$ in Stage I in order to maximize $E[U_{SP}]$. Because the social planner serves in the physician role also, $\eta_{s_r,s_t}$ is identical to $\phi_{s_r,s_t}$ in the first-best.

Define the following thresholds for $\mu$:

\[
T_{HH} := \frac{(1-\lambda)r_h t_h c_{FP}}{\lambda r_t u_d}, \quad T_{ LH} := \frac{(1-\lambda)(1-r_h)t_h c_{FP}}{\lambda(1-r_u)u_d},
\]
\[
T_{HL} := \frac{(1-\lambda)(1-t_h)c_{FP}}{\lambda r_u (1-t_u)d}, \quad T_{LL} := \frac{(1-\lambda)(1-r_h)(1-t_h)c_{FP}}{\lambda(1-r_u)(1-t_u)d}.
\]

These thresholds characterize the first-best follow-up policies for given signals, $s_r$ and $s_t$. For each $s_r,s_t$ pair, the numerator of the corresponding threshold captures the expected disutility in the case of a false-positive outcome while the denominator captures the same for a false-negative outcome.

The following lemma describes the optimal follow-up policies as a function of these thresholds.

**Lemma 1.** Given $s_r,s_t \in \{H,L\}$, social planner sets $\phi_{s_r,s_t} = 1$ if $T_{s_r s_t} < \mu$; $\phi_{s_r,s_t} = 0$ if $T_{s_r s_t} > \mu$; $\phi_{s_r,s_t} \in [0,1]$, otherwise.

Lemma 1 shows that a follow-up is recommended if and only if the expected benefit of the follow-up for an unhealthy patient is sufficiently high. The minimum $\mu$ required for recommending the follow-up depends on the signals. In the Appendix, we also show that $T_{HH} < T_{LH} < T_{HL} < T_{LL}$.

The order implies that the threshold $T_{s_r s_t}$ decreases when the risk and test information indicate a higher likelihood of the patient being unhealthy. This is intuitive because the expected benefit from the follow-up is higher for a patient with a higher likelihood, *ceteris paribus*. Table 2 characterizes the complete set of follow-up policies, where a value of 1 indicates a recommendation of follow-up for the patient and a value of 0 indicates a recommendation of no follow-up for the given $s_r,s_t$ combination.

<table>
<thead>
<tr>
<th>$s_r$</th>
<th>$s_t$</th>
<th>$\mu \leq T_{HH}$</th>
<th>$T_{HH} \leq \mu \leq T_{LH}$</th>
<th>Recommendation ($\eta_{s_r,s_t}$)</th>
<th>$T_{LH} \leq \mu \leq T_{HL}$</th>
<th>$T_{HL} \leq \mu \leq T_{LL}$</th>
<th>$T_{LL} \leq \mu$</th>
</tr>
</thead>
<tbody>
<tr>
<td>H</td>
<td>H</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>L</td>
<td>H</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>H</td>
<td>L</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>L</td>
<td>L</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Similar to the follow-up policies, the policies for screening in the first-best case are determined by several thresholds, provided below.

\[
S^n_H = S^n_L := u, \quad S^n_r := u - \frac{(1-\lambda)r_h t_{h,FPP}}{(1-\lambda)r_h + \lambda r_u + (1-\lambda)r_h}, \quad \frac{\lambda r_u t_u \mu d}{(1-\lambda)r_h + \lambda r_u + (1-\lambda)r_h},
\]

The thresholds \(S^n_r\) are determined based on \(s_r\) and the expected recommendation scenario, \(n\), in the follow-up stage. The scenario \(n = 0\) represents the case when the screened patient is never recommended a follow-up regardless of the test signal. The scenario \(n = 1\) represents the case when the screened patient is recommended a follow-up only when the test signal is high \((s_t = H)\). Finally, the scenario \(n = 2\) represents the case when the patient is always followed up regardless of the test signal.

**PROPOSITION 1.** The screening and follow-up policies in the first-best solution denoted as the triple \((\theta^*_s, \phi^*_s, \phi^*_s, \phi^*_s)\) are given in Table 3.

<table>
<thead>
<tr>
<th>Conditions</th>
<th>(\mu \leq T^{HH})</th>
<th>(T^{HH} \leq \mu \leq T^{LL})</th>
<th>(T^{LL} \leq \mu \leq T^{HL})</th>
<th>(T^{HL} \leq \mu \leq T^{LL})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_t \geq S^H_1)</td>
<td>((0, -,-))</td>
<td>((0, -,-))</td>
<td>((0, -,-))</td>
<td>((0, -,-))</td>
</tr>
<tr>
<td>(c_t \leq S^L_2)</td>
<td>(N/A)</td>
<td>(N/A)</td>
<td>(N/A)</td>
<td>(1,1,1)</td>
</tr>
<tr>
<td>(c_t \geq S^H_2)</td>
<td>(N/A)</td>
<td>((1,1,0))</td>
<td>(1,1,0)</td>
<td>(N/A)</td>
</tr>
<tr>
<td>(c_t \leq S^L_2)</td>
<td>(N/A)</td>
<td>((1,1,1))</td>
<td>(1,1,1)</td>
<td>(1,1,1)</td>
</tr>
</tbody>
</table>

(a) Policies when \(s_r = H\).

<table>
<thead>
<tr>
<th>Conditions</th>
<th>(\mu \leq T^{HH})</th>
<th>(T^{HH} \leq \mu \leq T^{LL})</th>
<th>(T^{LL} \leq \mu \leq T^{HL})</th>
<th>(T^{HL} \leq \mu \leq T^{LL})</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_t \geq S^L_1)</td>
<td>((0, -,-))</td>
<td>((0, -,-))</td>
<td>((0, -,-))</td>
<td>((0, -,-))</td>
</tr>
<tr>
<td>(c_t \leq S^L_2)</td>
<td>(N/A)</td>
<td>(N/A)</td>
<td>(N/A)</td>
<td>(1,1,1)</td>
</tr>
<tr>
<td>(c_t \geq S^L_2)</td>
<td>(N/A)</td>
<td>(N/A)</td>
<td>((1,1,0))</td>
<td>(1,1,0)</td>
</tr>
<tr>
<td>(c_t \leq S^L_2)</td>
<td>(N/A)</td>
<td>(N/A)</td>
<td>((1,1,0))</td>
<td>(1,1,1)</td>
</tr>
</tbody>
</table>

(b) Policies when \(s_r = L\).

Notes. We use “-” to denote the case where a policy is not applicable. We use “N/A” to denote the case when its corresponding condition is not applicable.
physician, i.e., $\phi^*_{HH}$, $\phi^*_{HL}$, $\phi^*_{HL}$, and $\phi^*_{LL}$ are non-decreasing in $\mu$, (ii) an increase in the cost of the test $c_t$ favors not recommending a patient to undergo the test, i.e., $\theta^*_H$ and $\theta^*_L$ are non-increasing in $c_t$, (iii) a patient with a high risk signal is more likely to be recommended to undergo the test than one with a low risk signal, i.e., $\theta^*_H \geq \theta^*_L$, and (iv) a patient with a high test signal is more likely to be recommended follow-up than one with a low test signal, i.e., $\phi^*_{HH} \geq \phi^*_{HL}$ and $\phi^*_{HL} \geq \phi^*_{LL}$.

In the parameter space, there are regions where either the risk information or the test information plays no role in determining the policies, i.e., there are regions where i) no patient is screened for testing (i.e., $\theta^*_H = \theta^*_L = 0$), ii) every patient that is tested is recommended a follow-up action (i.e., $\phi^*_{HH} = \phi^*_{HL} = \phi^*_{HL} = 1$), or iii) every patient is tested and then recommended a follow-up action based only on the test information (i.e., $\theta^*_H = \theta^*_L = 1$, and $\phi^*_{HH} = \phi^*_{HL} = 1$, $\phi^*_{LL} = \phi^*_{LL} = 0$). Clearly, these regions in the parameter space are either unrealistic or uninteresting. In the rest of the paper, for expositional clarity, we present the analysis and results for the region in the parameter space that satisfies the following assumption which ensures that both risk information and test information are useful in deciding the recommendation for the patient.

**Assumption 1.** $\underline{\mu} < \mu < T^{HL}$ and $c_t < c_t < S^H$,

where $\mu := \frac{(1-\lambda)r_h + \lambda r_u}{d\lambda r_u t_u} - \frac{(1-\lambda)\text{CFP}(\lambda t_h r_u^2 (1-t_u))}{d\lambda r_u^2 t_u (1-(1-\lambda)r_h - \lambda r_u)} + \frac{(1-\lambda)c_{FP}r_h t_h}{(1-\lambda)r_h - \lambda r_u - u} + \frac{(1-\lambda)\text{CFP}(\lambda r_h r_u (t_u ((1-t_h)(-r_u) - 2t_h + 1) + t_h))}{d\lambda r_u^2 t_u (1-(1-\lambda)r_h - \lambda r_u + 1)} + \frac{(1-\lambda)\text{CFP}(\lambda t_h (1-t_h)(1-t_u))}{d\lambda r_u (1-t_u)(1-(1-\lambda)r_h - \lambda r_u)}$.

The assumption states that neither the benefit nor the cost of health care service (i.e., testing) is too high relative to the other. The parameter space that satisfies Assumption 1 is shown as the shaded region in Figure 2. In the shaded region, only high-risk patients are sent to the physician and the physician recommends a follow-up only when the test information is also high.

### 4.2. No Litigation Case

In this case, the physician does not face any litigation concerns. The social planner determines the screening and follow-up policies, but the physician determines the actual recommendation for the patient and he could possibly deviate from the social planner’s policy in order to maximize his own payoff (i.e., $\phi_{s_o, s_t}$ and $\eta_{s_o, s_t}$ may be different). We use backward induction to derive the sub-game perfect equilibrium for the game. In Stage II, the physician determines the optimal decision $\eta_{s_r, s_t}$ after observing signals $s_r$ and $s_t$ and the social planner’s policies. Anticipating the physician’s choice of $\eta_{s_r, s_t}$ in Stage II, the social planner chooses the optimal screening policy $\theta_{s_r}$ for each $s_r \in \{H, L\}$ and the optimal follow-up policy $\phi_{s_o, s_t}$ for each $s_o, s_t \in \{H, L\}$ in Stage I of the game.
Proposition 2. When malpractice litigation is not a concern for the physician, the social planner induces the first-best solution.

Proposition 2 is significant because it shows that even when the physician’s objective differs from that of the social planner, the social planner is able to coordinate the physician’s actions through appropriate policies and achieve the first-best solution provided litigation is not a concern for the physician.

4.3. No Information Sharing Case

Clearly, the risk information combined with the test information is more informative than the test information alone in inferring the patient’s health. However, as we stated before, availability of risk information increases the litigation concern because it can be used as evidence in a lawsuit. In the no information sharing case, the risk information is not shared with the physician. Since we focus only on the information sharing role of health IT, this case could be viewed as corresponding to the case of no health IT. When the risk information of individual patients is not shared with the physician, the follow-up policy can only be based on the test signal and therefore the probability of the patient winning the lawsuit against the physician can only be influenced by the policy regarding the test signal. In effect, the likelihood of a successful lawsuit for this case reduces to

\[ f_0(\phi_{st}) = b_{st} \phi_{st}. \]

We also note that, under no information sharing case, physician loses the discriminative power in determining the patient’s health in some cases (e.g., when \( T^{HL} < \mu \) and \( c_t < S_{Lt} \)). Hence, the loss of value (in terms of physician’s follow-up decision performance) due to absence of health IT (no information sharing case) is already incorporated into the analysis. Because physician’s follow-up decisions can improve under information sharing as compared with no information sharing, the overall likelihood of a lawsuit, which is a function of false-negative cases, will also be lower.

Proposition 3. When risk information is not shared with the physician, the social planner induces the first-best solution.
Proposition 3 reveals that even when the physician’s objective differs from that of the social planner and litigation is a concern for the physician, the social planner is able to coordinate the physician’s actions through appropriate policies and achieve the first-best solution if the risk information is not shared with the physician. The current subsection together with Section 4.2 provides a benchmark for the analysis of the information sharing and litigation scenario, which we analyze next.

4.4. Litigation and Information Sharing Case

Under this setup, the physician faces a lawsuit in the case of a false-negative outcome, and the patient’s risk information is shared with him. Therefore, both the social planner and the physician account for the cost/disutility arising from litigation while making the decisions based on the available information. Let

\[
\bar{T}_{sr,st} := T_{sr,st} - \frac{(1-2\alpha)kf(\theta_{sr},\phi_{sr,st})+(1-\alpha)l}{\alpha d}, \text{ for } (s,r,s_t) \in \{(HL),(LH)\}.
\]

(3)

We note that \( \bar{T}_{sr,st} < T_{sr,st} \) holds.

**Lemma 2.** Physician’s decisions in Stage II under litigation concern and information sharing are as follows.

1. \( \eta_{LL} = 0, \eta_{HH} = 1 \).

2. If \( \bar{T}_{LH}(\theta_L,\phi_{LH}) < \mu \), then \( \eta_{LH} = 1 \); otherwise, \( \eta_{LH} = 0 \).

3. If \( \bar{T}_{HL}(\theta_H,\phi_{HL}) < \mu \), then \( \eta_{HL} = 1 \); otherwise, \( \eta_{HL} = 0 \).

Lemma 2 reveals that for any set of policies, the physician always recommends follow-up if both risk and test information are high; never recommends a follow-up if both information are low; and, in other cases, recommends a follow-up if and only if the patient’s relative benefit from the follow-up exceeds a threshold value, as in the first-best case. We further find that the threshold for \( \mu \) for recommending follow-up in the litigation and information sharing case is smaller than that in first-best case when a) \( s_r = L \) and \( s_t = H \) or b) \( s_r = H \) and \( s_t = L \). That is, when there is a litigation concern, under information sharing, physicians lower the threshold for follow-up, compared with the no litigation case, which indicates the practice of defensive medicine (Studdert et al. 2005).

Lemma 2 also reveals a key insight that highlights the enhanced vulnerability and the consequent defensive behavior of the physician resulting from information sharing. Figure 3 illustrates this insight by comparing the physician’s decisions under the first-best case and the case with litigation concern under information sharing. It shows that physicians will behave defensively only when the test and risk information indicate conflicting signals, but not when both indicate the same signal. The dependence of defensive behavior on signal discrepancy is because when the signals are consistent (both are high or low), the physician is highly certain about the patient’s health condition, and therefore litigation
Figure 3 An Illustration of Lemma 2

Notes. The figure compares follow-up decisions under the first-best scenario \((s_r, s_t)\) and the follow-up decisions under the litigation scenario \((\eta_{s_r}, \eta_{s_t})\) for a given information set, \(\theta_{s_r} > 0\) and \(s_r, s_t \in \{L, H\}\). Shaded areas represent the cases where the follow-up decision in the litigation scenario differs from that in the first best.

concern is not strong enough to alter his decision. On the other hand, conflicting signals increase the physician’s uncertainty in making a recommendation; when the benefit from the follow-up is moderate, i.e., if \(T^{LH}(\theta_L, \phi_L, H) < \mu < T^{LL}(\theta_L, \phi_L, L)\) or \(T^{HL}(\theta_H, \phi_L, H) < \mu < T^{HL}(\theta_H, \phi_L, L)\), the litigation concern alters the physician’s recommendation from no follow-up to follow-up. We further note that the physician faces the possibility of conflicting information only because of information sharing. The primary implication of this finding, combined with findings from Section 4.3 is that the sole reason for the physician’s practice of defensive medicine in our model is the sharing of risk information with the physician.

We denote the equilibrium under litigation concern as \([((\theta^*_H, \phi_{HH}^*, \phi_{HL}^*, \eta_{HH}^*, \eta_{HL}^*), (\theta^*_L, \phi_{LH}^*, \phi_{LL}^*, \eta_{LH}^*, \eta_{LL}^*))]\) and define the following thresholds to characterize the equilibria in this case.

\[
\begin{align*}
T_1 &= T^{HL}_{\theta=1, \phi_{HL}=1}, \quad T_2 := T^{HL}_{\theta=1, \phi_{HL}=0}, \quad T_3 := T^{HL}_{\theta=0, \phi_{HL}=0} \\
\end{align*}
\]

PROPOSITION 4. Equilibrium decisions under litigation concern are given by Table 4.

Figure 4 illustrates Proposition 4 and facilitates comparison of the equilibria in the first-best case and the case with information sharing and litigation concern.\(^5\) A comparison of Proposition 4 and Proposition 1 provides several key insights about the implications of litigation concern on the social planner and the physician, which we discuss in detail below.

\(^5\) In order to illustrate all possible equilibrium decisions, Figure 4 assumes the impact of litigation on a decision maker’s behavior is not too strong. If the impact is extremely strong, the physician would always practice defensive medicine regardless of the social planner’s decision. Also, the social planner would screen no patient at all.
Table 4  
Equilibrium under the litigation concern \([\theta_H^L, \phi_H^L, \phi_H^L, \eta_H^L, \eta_H^L, \eta_H^L, \eta_H^L, \eta_H^L] \).  

<table>
<thead>
<tr>
<th>Conditions</th>
<th>(\mu \leq T_1)</th>
<th>(T_1 &lt; \mu \leq T_2)</th>
<th>(T_2 &lt; \mu \leq T_3)</th>
<th>(T_3 &lt; \mu)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(c_t \geq S_2^H)</td>
<td>(c_t \geq S_2^H)</td>
<td>({(0,\cdot,\cdot,\cdot,\cdot)})</td>
<td>({(0,\cdot,\cdot,\cdot,\cdot)})</td>
<td>({(0,\cdot,\cdot,\cdot,\cdot)})</td>
</tr>
<tr>
<td>(c_t \leq S_2^H)</td>
<td>({(1,1,0,1,1),(0,\cdot,\cdot,\cdot,\cdot)})</td>
<td>({(1,1,0,1,1),(0,\cdot,\cdot,\cdot,\cdot)})</td>
<td>({(0,\cdot,\cdot,\cdot,\cdot)})</td>
<td></td>
</tr>
</tbody>
</table>

Notes. \(\theta_1 = \frac{(1-\lambda)\varphi_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP}}{1 - 2\lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP}}\),
\(\bar{\theta}_1 = \frac{(1-\lambda)\rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP}}{1 - 2\lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP} + \lambda \rho_{PP}}\).

Figure 4  
The equilibrium under information sharing and litigation case.

Notes. Shaded areas (Regions A, B, C, and D) represent the cases where the solution in the litigation and information sharing case differs from that of the first best. In particular, A is the area where only a fraction of high-risk patients are sent to the physician (corresponding to \(5\) in Table 4). B is the area where all or a fraction of high-risk patients are sent to the physician depending on parameter values (corresponding to \(7\) in Table 4). C is the area where no patient is sent to the physician (corresponding to \(1\) in Table 4). D is the area where all high-risk patients are sent to the physician, but the physician behaves more defensively due to the litigation concern (corresponding to \(3\) and \(8\) in Table 4). In the remaining area, the solutions are the same as in the first best (corresponding to \(4\) in Table 4), but the social utility is lower because of litigation. The other cases in Table 4 (\(2\), \(6\)) do not exist in this illustration.

(i) Inability to Induce First-Best Solution

The observation that Table 4 and Table 3 are not identical (for the relevant parameter region) shows that the social planner is unable to induce the first-best solution under information sharing when litigation is a concern for the physician. Additionally, the following observation is worth highlighting. The first-best policies and first-best physician decisions remain optimal even under the litigation concern when \(\mu\) and \(c_t\) are low enough (when \(\mu \leq T_2\) and \(c_t \leq S_2^H\), the unshaded region in Figure 4 and region \(4\) in Table 4). However, despite the optimality
of first-best decisions, the social utility under the litigation and information sharing case is inferior to the first best because the litigation cost associated with a false-negative outcome reduces the social utility. This finding implies that, in region 4, even though the social planner’s policies eliminate the defensive medicine practice, they are inadequate to achieve the first-best social welfare. Therefore, the social planner needs to employ additional strategies to mitigate the adverse effects of litigation in this region (e.g., Section 6 analyzes one such strategy, viz., a tort strategy that limits the compensation in a litigation case).

(ii) Inducing Defensive Medicine Practice

The litigation concern may induce defensive practices. For instance, in Regions 3 and 8 in Table 4 and area D in Figure 4, the social planner sets the same screening policies as those in the first-best but he is unable to control the physician’s defensive behavior. In particular, in these regions, instead of the socially optimal decision of recommending the follow-up only for those patients that have a high test signal, the physician recommends the follow-up for everyone including patients with a low test signal because of the litigation concern. This observation reveals that the social planner is unable to eliminate defensive medicine through his policies under some conditions.

(iii) Underprovisioning of Health Care

A key consequence of legal vulnerability created by information sharing is the possible underprovisioning of health care. The underprovisioning manifests itself in two ways:

(A) In some cases, the social planner does not recommend a patient to undergo testing under litigation concern and information sharing even though he would recommend the high-risk patient to undergo testing in the first-best case (see for example regions 1 and 6 in Table 4 and area C in Figure 4). More specifically, a relatively high cost of testing compared with the benefit makes screening recommendation undesirable as the social planner anticipates that the physician is going to behave defensively. Thus, the social costs associated with the litigation may offset the benefit of testing in this region, causing the social planner to under-screen patients.

(B) Consider regions labeled as 5 and 7 in Table 4 (or regions A and B in Figure 4). In the entire region 5, and in part of region 7 depending on parameter values, only a fraction of the high-risk patients are recommended for testing. These regions characterize moderate values of $\mu$ and low to moderate values of $c_t$. The intuition for this result is as follows. When the benefit from screening and possible follow-up is moderate for a high-risk patient, the social planner recommends screening and prefers the physician to follow up the patient when the test signal is high and not follow up when the test signal is low. However, for the physician, the litigation cost from a possible false-negative outcome
offsets the moderate benefit of follow-up action to the patient; therefore, the physician is inclined to recommend follow-up regardless of the test signal and the social planner’s guideline. That is, litigation concern becomes the over-riding factor in the physician’s recommendation. Not being able to control the defensive behavior through follow-up policies to the physician, the social planner is left with tweaking the screening policy to mitigate the defensive medicine practice for social good. The physician’s expected cost of litigation is influenced by two factors that depend on the social planner’s screening guidelines: (i) the likelihood of the patient winning the lawsuit, and (ii) the probability of the screened patient being unhealthy. Both the factors are reduced by a decrease in $\theta_H$, and therefore the social planner decreases $\theta_H$ from one. However, decreasing $\theta_H$ has a harmful effect in that it increases the false-negatives for those patients that are not screened. In other words, a reduction in $\theta_H$ implies that some patients with the high-risk signal are not recommended to undergo the testing, hence underprovisioning of health care. The trade-offs between these two effects lead to the equilibrium policy indicated for this region.

In summary, our findings reveal the following. (i) Health IT, particularly the information sharing aspect of it, creates additional legal vulnerability. (ii) The possible conflict created by shared information is the source of the vulnerability due to health IT. (iii) The vulnerability may have the sole effect of increased litigation cost or social utility loss without affecting either the social policies or the physician actions. (iv) In line with the conventional wisdom that the litigation fear fuels defensive medicine, the increased liability risk due to health IT leads to overutilization of health care services. (v) For some high-risk patients, however, underprovisioning of health care services can be the solution for countering the increased risk of legal liability due to health IT.

4.5. Impact of Information Precision and Physician Benevolence

The impact of information sharing under litigation concern depends critically on the precisions of the risk and test information and the degree of physician benevolence. In this section, we study how information precision and physician benevolence affect the policy decisions, especially in the region where health IT leads to underprovisioning of health care. Note that such an assessment is pertinent because the advances in health IT continually improve the quality of patient risk information while advances in medical technology improve the testing capabilities.

**Proposition 5.** In the equilibrium region where underprovisioning occurs,

1. $\frac{\partial q_t^*}{\partial r_u} < 0, \frac{\partial q_t^*}{\partial r_h} > 0$: As sensitivity or specificity of the risk information increases, fewer patients are recommended for testing.
2. $\frac{\partial q_t^*}{\partial r_u} > 0, \frac{\partial q_t^*}{\partial r_h} < 0$: As sensitivity or specificity of the test information increases, more patients being recommended for testing.
Intuitively, one would expect that a more precise signal, whether it is the risk signal or the test signal, would motivate the social planner to recommend more high-risk patients for testing. However, Proposition 5 shows that while the above intuition holds for the test signal, the opposite result holds for the risk signal. To understand this counter-intuitive observation, we first examine how the physician behavior changes with respect to \( r_u \) and \( r_h \); in other words how \( \tilde{T}^{HL}(\theta_H, \phi_HL) \) changes with the precision of risk information. We find that the threshold \( \tilde{T}^{HL} \) decreases as the sensitivity or the specificity of risk information increases because an improvement in the quality of the risk information relative to that of test information causes the physician to put more weight on the risk information while making his recommendation. Therefore, the physician will more likely recommend follow-up when the risk is high and would practice defensive medicine more when either \( r_u \) or \( r_h \) increases. As was discussed after Proposition 4, the social planner can mitigate the defensive medicine practice by decreasing \( H \). But, an increase in the risk information precision exacerbates the defensive medicine behavior, and, as a result, the social planner decreases \( \theta_H \). On the other hand, an increase in the test signal’s precision relative to that of risk signal diminishes the importance of the risk information. Therefore, an improvement in test signal precision has the opposite effect on the social planner’s policies as compared to the effect of an improvement in the precision of risk information.

We also conduct a comparative statics analysis regarding \( \alpha \) which is the parameter that captures how much the physician values the patient utility in comparison to his own. Even though physicians aim to deliver the best care to their patients, financial incentives or ethical judgment could also play a role in their practice (Chandra and Skinner 2012). The variation in physicians’ valuation of patient health vs. other factors could also moderate the impact of litigation on the overall utility (Chandra and Skinner 2012, Clemens and Gottlieb 2014). Hence, the trade-offs affecting the formulation of social policies could vary. To see the impacts of \( \alpha \) on the physician’s behavior and the under-provisioning of health care, we take partial derivatives of \( \tilde{T}^{HL}(\theta_H, \phi_HL) \) and \( \theta_i \) with respect to \( \alpha \).

**Proposition 6.** *In the equilibrium region where underprovisioning occurs, \( \frac{\partial i^*}{\partial \alpha} > 0 \), i.e., as the physician’s weight on the patient’s utility increases, more patients are recommended for testing.*

With more weight on the patient’s utility, the physician would suffer less from litigation. Note that, as we discussed in Lemma 2, the physician’s decision thresholds are shifted to the left on the horizontal line of \( \mu \) with an increase in litigation costs. When the physician puts less weight on the litigation costs compared to the patient’s utility, the degree of the shift is less. Anticipating the reduced deviation in thresholds, the social planner is less inclined to adjust \( \theta_H \) to cope with physicians’ defensive behavior if the physician is more benevolent. Therefore, the social planner recommends more patients to be tested based on the risk information when \( \alpha \) increases.
In summary, we find that the problems associated with the practice of defensive medicine and the consequent underprovisioning of health care become more severe when the quality of risk information increases relative to that of test information or the physician become less patient-oriented and more self-oriented.

5. Relationship to Empirical Observations

The analysis presented in the previous section provides several theoretical insights regarding how information sharing under litigation risk affects physician’s defensive behavior and the social policies. Naturally, two important questions that arise are how the social policies as modeled in this paper are operationalized in real life and whether the theoretical results are supported by empirical evidence. We discuss these in this section.

5.1. Operationalization of Screening and Follow-up Policies

A key mechanism by which a social planner implements his policies is through health care guidelines. In health care, it is standard practice to code various medical activities, including the use of health information, in the form of practice guidelines (Rosenfeld et al. 2013). In the following, we briefly summarize two ways guidelines can operationalize the policies indicated by our analysis.

(i) In our model, the social planner’s policies are indicated by the variables \( \theta \) and \( \phi \). Under socially optimal policies, these variables assume either a value of one, a value of zero, or a value between zero and one. The policy in which a variable has a value of one or zero (in other words, absolute recommendation) can be operationalized in practice using “rigid” guidelines, also referred to as the standard of care. An example of such a rigid guideline is all high-risk patients must be sent to a physician (a value of one) or no low-risk patient should be sent to a physician (a value of zero). In a manual prepared for the American Academy of Otolaryngology–Head and Neck Surgery, Rosenfeld et al. (2013) provide the following example of rigid guidelines for benign, paroxysmal positional vertigo: “Clinicians should treat patients with posterior semicircular canal benign, paroxysmal positional vertigo with a particle repositioning maneuver.” On the other hand, policies where those variables assume a value between zero and one can be operationalized using “flexible” guidelines. An example of a flexible guideline is the one recommending that a high-risk patient may be sent to a physician. In particular, a mechanism by which a flexible guideline is operationalized is through the usage of a somewhat vague language that gives more flexibility to physicians in guidelines (Rosenfeld et al. 2013, Shiffman et al. 2009, Warren et al. 2000). For example, the current USPSTF guidelines in mammography screening for women between the ages of forty and fifty recommend that “biennial screening

\[ ^6 \text{We suppress the subscripts and superscripts for brevity.} \]
mammography should be an individual one and take patient context into account” (Siu 2016). Moreover, it is worth pointing out that Warren et al. (2000) suggest an algorithm that handles vague or ambiguous language when designing and implementing an automated decision support based on guidelines, which could be helpful in measuring the level of vagueness that would be consistent with the desired flexibility in our modeling.

(ii) Another mechanism to operationalize policies, especially those related to flexible guidelines, is to utilize multiple rigid guidelines simultaneously. One good example to this is the existence of multiple guidelines in breast cancer screening. For instance, while USPSTF guidelines recommend biennial screening for women between the ages of 50-74, the American Cancer Society guidelines recommend annual screening for all women over age 40 (American Cancer Society 2015). Although the pluralism in guidelines is different from the flexibility (Havighurst 1989, Mello 2001), these multiple rigid guidelines may have the same effect as in a single flexible guideline with vague language by providing more flexibility to physicians in their decisions. Incorporating multiple guidelines into decision support systems can create the desired effect because the differences in guidelines can assuage defensive behavior as physicians can rely on the guideline of their choice.

Both of the above mechanisms of how a social planner can translate our policy findings into practice are already realities of actual medical care. They demonstrate that the findings of our work can be operationalized. Further, our discussion of guidelines as possible tools for policy making can inform the debates around medical guideline design, defensive medicine, and over- or underprovisioning of health care services (e.g., Kaamoto and Greenes 2011, Rosenfeld et al. 2013, Schwartz et al. 2014, Grady and Redberg 2010).

5.2. Empirical Observations
In this subsection, we apply our model to the breast cancer context, and demonstrate how the model predictions compare with empirical observations. Further, we also quantify the effect of defensive medicine and litigation risk arising from health IT in breast cancer screening. We choose breast cancer screening example because i) breast imaging is the most common cause of medical malpractice claims in the United States (Anderson and Troxel 2005), ii) the subject has been studied extensively and thus good estimates for most of the model parameters are available in the published literature.

Based on individualized risk calculations, women are recommended mammography screening for breast cancer (Saslow et al. 2007, Moyer 2012). The widely used Gail model evaluates a patient’s risk of developing breast cancer based on various risk factors (Tice et al. 2008). The model categorizes patients into average-risk and high-risk groups (risk information). Guidelines use these risk groups to communicate screening recommendations to patients (e.g., see Siu 2016). Extensive randomized
controlled trials and observational studies provide data regarding the specificity and sensitivity of mammography (test information) (e.g., see Pisano et al. 2005). Furthermore, various health economics studies provide utility and cost data associated with the modeled outcome scenarios (e.g., see Studdert et al. 2005, Tosteson et al. 2008). Based on these databases, Table 5 provides the point and interval estimates for different parameter values we use to illustrate our theoretical results as well as the references for these estimates. While robust data and thus reliable estimates are available

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Sources</th>
<th>Comments</th>
<th>Estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>Tice et al. (2008)</td>
<td>1,095,484 women age 35 years or older</td>
<td>0.013</td>
</tr>
<tr>
<td>$r_a$</td>
<td>Tice et al. (2008)</td>
<td>variants of Gail model</td>
<td>0.525</td>
</tr>
<tr>
<td>$r_b$</td>
<td>Tice et al. (2008)</td>
<td>variants of Gail model</td>
<td>0.315</td>
</tr>
<tr>
<td>$t_a$</td>
<td>Newton and Grethlein (2016)</td>
<td>screening mammography</td>
<td>0.726</td>
</tr>
<tr>
<td>$t_b$</td>
<td>Newton and Grethlein (2016)</td>
<td>screening mammography</td>
<td>0.239</td>
</tr>
<tr>
<td>$c_i$</td>
<td>Ayvaci et al. (2012), Centers for Medicare and Medicaid Services (2014), Tosteson et al. (2008)</td>
<td>$c_i$ includes disutilities from mammography, reimbursements to a radiologist, and office visit costs</td>
<td>$428 \pm 173$</td>
</tr>
<tr>
<td>$c_{FF}$</td>
<td>Gram et al. (1990)</td>
<td>screening mammography</td>
<td>$5,609 \pm 4,369$</td>
</tr>
<tr>
<td>$u$</td>
<td>Centers for Medicare and Medicaid Services (2014), Tosteson et al. (2008)</td>
<td>$u$ includes reimbursements to a radiologist, and office visit costs</td>
<td>$248 \pm 124$</td>
</tr>
<tr>
<td>$d$</td>
<td>Wu et al. (2011)</td>
<td>quality of life year loss</td>
<td>$671,303 \pm 578,585$</td>
</tr>
<tr>
<td>$l$</td>
<td>Studdert et al. (2006)</td>
<td>defense costs</td>
<td>$50,296 \pm 15,354$</td>
</tr>
<tr>
<td>$k$</td>
<td>Studdert et al. (2006)</td>
<td>amount of compensation paid</td>
<td>$432,342 \pm 174,343$</td>
</tr>
<tr>
<td>$\mu$</td>
<td>Hendrick and Helvie (2011)</td>
<td>mortality reduction by screening mammography for women age younger than 50</td>
<td>0.145</td>
</tr>
<tr>
<td></td>
<td>Hendrick and Helvie (2011)</td>
<td>mortality reduction by screening mammography for women age 50 or older than 50</td>
<td>0.235</td>
</tr>
</tbody>
</table>

Notes. We use a willingness-to-pay ratio with range $28,300$–$381,500 to obtain a single measure (King et al. 2005). All utility values are adjusted to reflect 2015 dollars.

For most model parameters, we do not have good estimates for a few parameters; namely $a_{HL}$, $b_{HL}$, and $\alpha$. For these parameters, we assume the following baseline values: $a_{HL} = 0.20$, $b_{HL} = 0.6$, and $\alpha = 0.175$ in our illustration. In addition to using these baseline values, we further conduct extensive sensitivity analysis using the following ranges for these variables ($a_{HL} \in [0.115, 0.40]$, $b_{HL} \in [0.0, 0.85]$, $\alpha \in [0.078, 0.186]$). The results from our sensitivity analysis reveal that the results are quite robust against relative changes in these parameter values.

We illustrate Proposition 4 using Figure 5. We use an interval estimate of $250 \sim 600$ for $c_i$, which includes office visit costs, reimbursements to a radiologist, and disutility from mammography including lost working hours, converted into U.S. dollars. In addition, we take 0.10 as a lower bound and 0.30 as an upper bound of $\mu$, following Hendrick and Helvie (2011). Using these values, we characterize the equilibrium decisions on screening policies as in Figure 5. As seen in Figure 5(a), we find that when cost of screening is moderate $c_i ($428), the impact of litigation risk on screening policy is twofold. First, it is optimal to send only a fraction of high-risk patients for mammogram (and no low-risk patients are screened) when $0.23 < \mu < 0.30$ (e.g., underprovisioning policy). Also, no patient should be screened when $\mu < 0.17$. In the absence of litigation risk, all high-risk patients
Notes. We label a policy as standard screening when the policy recommends screening for only the high risk patients and as no-screening when neither the high-risk nor the low-risk patients are recommended for screening. Each region in subfigure (a) is labeled with corresponding screening policy. The regions for no-screening and underprovisioning screening policy are the result of litigation risk, and differ from the first-best screening policy. The dotted, dashed, and long dashed-dotted lines in subfigure (b) represent cut-off values between non-screening and screening of high-risk patients when $c_t$ takes low, moderate, and high values, respectively. 

would be screened when $0.14 < \mu < 0.30$ (e.g., standard screening policy) and no patient would be screened when $\mu < 0.17$ (standard no screening policy). We also find that the fraction of high-risk patients that should be recommended to get mammography decreases from 99.99% when $\mu = 0.23$ to 84.43% when $\mu = 0.30$ (see Figure 5(b)). We obtain qualitatively similar results when $c_t$ varies.

A comparison of our model predictions to the breast cancer screening guidelines proposed by the USPSTF provides some interesting observations. In particular, the USPSTF guidelines recommend that 1) women older than fifty get biennial screening (standard screening policy), 2) for women between the ages forty and fifty, “biennial screening mammography should be an individual one and take patient context into account” (an underprovisioning policy using a flexible guideline), and that 3) women younger than forty be not screened (standard no screening policy) (Siu 2016). The rationale provided for these recommendations was that breast cancer mortality reduction due to mammography, a factor captured by parameter $\mu$ in our model, is age based and increases with age. In that regard, the USPSTF recommendations are consistent with our identified relationship regarding the fraction of high-risk patients that would be recommended to see the physician as the benefit from screening increases. Despite the seeming consistency between model predictions and the guidelines, we cannot conclude that the policy makers in USPSTF take into account the litigation concerns and impact of information sharing on litigation vulnerability while formulating their guidelines. On the other hand, health care policy discussions suggest the use of policy recommendations leading to underprovisioning (i.e., those operationalized through flexible guidelines) in clinical practice for reasons such as insufficient medical evidence, lack of consensus within the health care community,
cost, and, more importantly, concern over setting a legally binding standard (Rosenfeld et al. 2013, The Office of Technology Assessment (OTA) 1994). Regarding its relation to legal issues, the clinical policy manual prepared by Rosenfeld et al. (2013) states that flexibility in guidelines may reflect the guideline designer’s “unwillingness to create a potential legal standard of care.” Furthermore, flexibility can “limit the usefulness of guidelines” as legal evidence in holding the physician responsible for deviating from them (The Office of Technology Assessment (OTA) 1994). This is because flexible guidelines do not allow evidence to be treated as completely exculpatory or inculpatory for determining the physician’s responsibility for a false decision. That is, besides the inherent uncertainty in the medical evidence itself, flexibility in guidelines also introduces uncertainty in the outcome of a medical lawsuit (Leahy 1989, Mello 2001), mitigating the litigation risk.

Next, we assess the impact of taking the litigation concerns into account in policy formulation. For this purpose, we quantify the benefit of optimal screening (which accounts for litigation concerns) over sending all high risk patients for mammogram. More specifically, we compute this benefit by calculating the social welfare difference between the two sets of policies in the region where underprovisioning is optimal, i.e., $0.23 < \mu < 0.30$ (see Figure 5(a)). Then, we divide this difference by the social welfare under the policy that recommend mammogram for all high-risk patients so that the impact is measured in terms of a percentage change. We find that, by accounting for the litigation concerns and underprovisioning care, the social welfare may be increased by $8.62 \sim 10.06\%$. Figure 8 in the Appendix shows benefits of similar magnitude for various values of $\mu$ and $c_t$.

Finally, we quantify the overtreatment rate caused by litigation concern and underprovisioning resulting from (optimal) guidelines for women older than 50 where mortality reduction rate ($\mu$) by screening mammography is estimated as 23.5% (Hendrick and Helvie 2011).\footnote{In the published literature, the estimated mortality reduction rate ranges from 0% to 46%, and we choose a moderate estimate.} If litigation is not a concern, according to the first-best policy, 24.95% of high-risk patients would get follow-up treatment. However, if the same first-best solution is used, under litigation concern, the physicians would recommend follow-up treatment for 100% of the high-risk patients. On the other hand, if the social planner follows underprovisioning, then 24.45% of high-risk patients would get follow-up treatment. The analysis suggests that underprovisioning of health care can offer substantial societal value when the physicians face litigation concern and health information sharing is ubiquitous.

6. Role of Malpractice Caps

While social policies that deal with health care provisioning have been debated extensively to deal with litigation concerns, tort reform, especially limit on malpractice damages and stricter definition of what constitutes medical malpractice, has historically been the primary strategy to address
physicians’ litigation concern (Kachalia and Mello 2011). Although tort reforms are still controversial (Kachalia and Mello 2011), it has been reported that the malpractice caps on damages were effective in dealing with the litigation cost (Hyman et al. 2009). In this section, we examine the impact of malpractice restrictions on social policies under information sharing. This examination is especially relevant in light of our finding that in some regions of the parameter space (namely 4 in Table 4), the social planner is unable to change the physician’s defensive medicine behavior through his policies.

In the baseline model, the physician provides a compensation of $k$ to the patient if the patient wins the lawsuit which results in an expected damage payment of $k f(\theta_{sr}, \phi_{sr}, s_t)$ by the physician. In this extension, we assume that the expected litigation payment is limited to $k$. The limit can be the result of a cap on $k$ or restrictions on the criteria used to determine medical malpractice. We define the thresholds for follow-up decisions when $s_r = H$ and $s_t = L$ as:

\[
T_1 = THL - \frac{(1 - \alpha)l + (1 - 2\alpha)\min[k(a_{HL} + b_{HL}), k]}{ad},
\]

\[
T_2 = THL - \frac{(1 - \alpha)l + (1 - 2\alpha)\min[k(a_{HL}), k]}{ad}.
\]

Then, the optimal equilibria under the damage cap are given in the Proposition 7.

**Proposition 7.** Equilibrium decisions with damages cap for litigation $[(\theta_H, \phi^*_H, \phi^*_HL, \eta^*_HH, \eta^*_HL)]$, $((\theta^*_L, \phi^*_LH, \phi^*_LL, \eta^*_LH, \eta^*_LL))$ are given in Table 6.

<table>
<thead>
<tr>
<th>Conditions</th>
<th>$\mu \leq T_1$</th>
<th>$T_1 \leq \mu \leq T_2$</th>
<th>$T_2 \leq \mu \leq T_3$</th>
<th>$T_3 \leq \mu \leq THL$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_t \geq S^H_1$</td>
<td>$c_t \geq S^H_1$</td>
<td>1 $[(0, \cdots, \cdots), (0, \cdots, \cdots)]$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$c_t \leq S^H_1$</td>
<td></td>
<td>2 $[(1,1,1,1), (0, \cdots, \cdots)]$</td>
<td>3 $[(1,1,1,1), (0, \cdots, \cdots)]$</td>
<td></td>
</tr>
<tr>
<td>$c_t \geq S^H_2$</td>
<td></td>
<td>4 $[(1,1,0,1,0), (0, \cdots, \cdots)]$</td>
<td>5 $[(\theta_t, 1,0,1,0), (0, \cdots, \cdots)]$</td>
<td>6 $[(0, \cdots, \cdots), (0, \cdots, \cdots)]$</td>
</tr>
<tr>
<td>$c_t \leq S^H_2$</td>
<td></td>
<td></td>
<td>7 if $\theta_t \geq \bar{\theta}_t$, $[(\theta_t, 1,0,1,0), (0, \cdots, \cdots)]$, if $\theta_t \leq \bar{\theta}_t$, $[(1,1,0,1,1), (0, \cdots, \cdots)]$,</td>
<td>8 $[(1,1,0,1,1), (0, \cdots, \cdots)]$</td>
</tr>
</tbody>
</table>

Figure 6 illustrates Proposition 7. We find that, similar to the baseline case with no limit on malpractice damage, as long as the physician cannot be fully protected, i.e., $k > 0$, there are still cases where underprovisioning of health care is needed to deal with the defensive medicine that arises from the sharing of the risk information as indicated by region E in Figure 6. However, compared to the baseline case, the size of the region in the parameter space where underprovisioning is optimal is smaller when there is a limit on the malpractice damage. That is, the limit on malpractice damage
Figure 6 The Equilibrium under the Damage Cap

Notes. Shaded areas (Regions E and F) represent the cases when the equilibrium results differ from the baseline model where there is litigation concern but there is no damage cap. In particular, E is the area where underprovisioning could still be optimal but its size is smaller compared to area A and B of Figure 4 (corresponding 5 and 7 in Table 6). F is the area where the optimal screening guidelines are the same the first-best, but its size is larger compared to the baseline model (corresponding 1 in Table 6). In the non-shaded areas, there is no change in the results compared to the baseline model.

lessens the need for underprovisioning of health care in these regions. On the other hand, the limit on malpractice damage does not have an impact in regions F and G. This finding is consistent with critics who argue against the effectiveness of the damage cap for reducing “frivolous lawsuits” and also with proponents who support its effectiveness in dealing with extreme cases (Hyman et al. 2009).

7. Discussion and Conclusion

We examine the issue of physician’s increased liability risk stemming from the sharing of health information using IT. We show that when malpractice litigation is not a concern or when risk information is not shared with the physician so that the physician is not faced with conflicting pieces of evidence about the patient’s health, the social planner can induce the first best solution that maximizes the social welfare. On the other hand, when litigation is a concern and patient risk information is shared with the physician—both of which are commonly observed in practice—the social planner is unable to do induce the first best solution. In particular, information sharing under litigation concern can lead to underprovisioning of health care for high-risk patients. We further show that malpractice damage caps may mitigate, but not eliminate, the need for under-provisioning.

Our findings also have several implications for health policy makers regarding the meaningful use of health IT and policies in the presence of litigation vulnerability created by widespread information sharing. The policies are articulated through guidelines. While guidelines affect the actions of health care providers’ medical recommendations to the patient, since 1990s, there have been extensive discussions on designing policies and guidelines that serve as legal standards (Woolf 1998, Sullivan 2015). Although guidelines are already admissible in many liability cases (Samanta et al. 2006, Mello
2001), the question regarding whether the guidelines should be conclusive or not for the purpose of reducing cost of defensive medicine is still unanswered (Sullivan 2015, Mehlman 2012, Rosenfeld et al. 2013). Some of the existing studies already advocate the use of flexible guidelines to provide the physician the autonomy to accommodate patients’ individual circumstances and different views on care practice (Leahy 1989, Woolf 1998, Rosenfeld et al. 2013, Samanta et al. 2006). However, such flexibility can also lead to underprovisioning or overprovisioning of health care. Our research shows that flexible guidelines that leads to underprovisioning may indeed be needed to deal with the litigation risk introduced by the increased data sharing, as it reduces the usefulness of the guideline in supporting the litigation claim (Liang 2015). The U.S. government recently considered the implementation of a new litigation policy that makes physicians immune to many frivolous litigation claims (Sullivan 2015, Mehlman 2012). However, as our findings suggest, a rigid guideline that provides too much safe harbor may potentially do more harm than benefit to the society in the era of widely shared health information, and the conduct of a cost-benefit analysis is a prerequisite to the implementation.

While data sharing among providers is being touted as a key strategy to improve care quality and decrease costs, our findings suggest that there is a critical need to examine the litigation concerns raised by such data sharing (Mangalmurti et al. 2010). Moreover, the risk information is sometimes handled by patients through patient portals and not by physicians (Ozdemir et al. 2011, Romanow et al. 2012). Our findings imply that no-information sharing could be the strategic choice with rigid guidelines if policy implementation could fully control the sharing of risk information. If not, a flexible guideline should be considered as an alternative to deal with the defensive medicine that emanates from information sharing.

From the perspective of managing health care organizations, guidelines are increasingly serving as tools to control the utilization of care resources (Green 2012). The recent reforms in the U.S. health care system is emphasizing a shift towards eliminating costs associated with unnecessary care and improving care quality through care coordination programs such as Accountable Care Organizations (ACOs). The key to the success of coordination is the development of effective care protocols to standardize care. This is because care protocols such as guidelines specify in which conditions limited resources should be used while considering the trade-offs between the associated costs and benefits (Green 2012). In that regard, our paper characterizes the conditions where flexible guidelines could be a solution to the over-utilization problem under the increased litigation risks emanating from information sharing.

To the best of our knowledge, this study is the first attempt to analyze one of the new adverse effects of health information sharing by using an economic model. The model captures the underlying proliferation of defensive medicine subsequent to wider health information sharing. The study can be extended in several directions. We consider defensive medicine only in the physician’s decisions,
and we do not explicitly model the agent who could possibly screen a patient in Stage I. Therefore, modeling agent’s decisions for could provide richer implications. Also, we consider a monopoly health care market and do not consider the impact of the policies on the market competition among physicians as the screening or follow-up policy has an impact on competing health systems (Nam et al. 2010), which could be the topic of a future extension study.

References


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### Appendix. Additional Figures and Tables

#### Table 7  Summary of notations

<table>
<thead>
<tr>
<th>Notation</th>
<th>Definition</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda$</td>
<td>probability that the patient is unhealthy</td>
<td>$\lambda \in (0,1)$</td>
</tr>
<tr>
<td>$s_r$</td>
<td>the signal about the patient’s health from the risk information</td>
<td>$s_r \in {H,L}$</td>
</tr>
<tr>
<td>$s_t$</td>
<td>the signal about the patient’s health from the test information</td>
<td>$s_t \in {H,L}$</td>
</tr>
<tr>
<td>$r_u$</td>
<td>sensitivity of the risk information</td>
<td>$r_u \in (0,1)$</td>
</tr>
<tr>
<td>$t_u$</td>
<td>sensitivity of the test information</td>
<td>$t_u \in (0,1)$</td>
</tr>
<tr>
<td>$1-r_h$</td>
<td>specificity of the risk information</td>
<td>$1-r_h \in (0,1)$</td>
</tr>
<tr>
<td>$1-t_h$</td>
<td>specificity of the test information</td>
<td>$1-t_h \in (0,1)$</td>
</tr>
<tr>
<td>$v$</td>
<td>base utility of the patient from a true-negative assessment</td>
<td>$\mu \in (0,1)$</td>
</tr>
<tr>
<td>$\mu$</td>
<td>treatment effect from a true-positive assessment</td>
<td>$c_t &gt; 0$</td>
</tr>
<tr>
<td>$c_t$</td>
<td>cost of taking the test</td>
<td>$c_t &gt; u &gt; 0$</td>
</tr>
<tr>
<td>$u$</td>
<td>physician’s base benefit from providing health service</td>
<td>$c_{FP} &gt; 0$</td>
</tr>
<tr>
<td>$c_{FP}$</td>
<td>over-treatment cost from a false-positive assessment</td>
<td>$d &gt; 0$</td>
</tr>
<tr>
<td>$d$</td>
<td>cost of a false-negative assessment</td>
<td>$l &gt; 0$</td>
</tr>
<tr>
<td>$l$</td>
<td>base litigation cost to the physician</td>
<td>$k &gt; 0$</td>
</tr>
<tr>
<td>$k$</td>
<td>compensation to the patient from the physician if the patient wins the lawsuit</td>
<td>$f(\theta_{sr}, \phi_{sr, st})$</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>relative weight of the patient’s utility in the physician utility</td>
<td>$\alpha \in (0,1)$</td>
</tr>
<tr>
<td>$\theta_{sr}$</td>
<td>screening policy</td>
<td>$\theta_{sr} \in [0,1]$</td>
</tr>
<tr>
<td>$\phi_{sr, st}$</td>
<td>follow-up policy</td>
<td>$\phi_{sr, st} \in [0,1]$</td>
</tr>
<tr>
<td>$\eta_{sr, st}$</td>
<td>physician’s recommendation to the patient</td>
<td>$\eta_{sr, st} \in [0,1]$</td>
</tr>
<tr>
<td>$U^i$</td>
<td>utility of physician ($i = PH$), patient ($i = PA$), or social planner ($i = SP$)</td>
<td>$i \in {PH, PA, SP}$</td>
</tr>
</tbody>
</table>
Figure 7  Patient pathways under the litigation scenario

Notes. SP: social planner, PH: physician, PA: patient. Under no-litigation scenario, the screened patient who was recommended a follow-up will incur the false-negative outcome.

Figure 8  Improvement of Social Welfare with the Underprovisioning Policy
Appendix. Utility Expressions and Proofs of Structural Results

Patient’s expected utility is given by

\[
E[U^{PA}] = \lambda r_u \theta_H (t_u \eta_{HH} d \mu + (1-t_u) \eta_{HL} d \mu - d - c_i) + \lambda r_u (1-\theta_H)(-d) \\
+ \lambda (1-r_u) \theta_L (t_u \eta_{HL} d \mu + (1-t_u) \eta_{LL} d \mu - d - c_i) + \lambda (1-r_u)(1-\theta_L)(-d) \\
+ (1-\lambda) r_u \theta_H [t_h \eta_{HH} (-c_{FP}) + (1-t_h) \eta_{HL} (-c_{FP}) - c_i] \\
+ (1-\lambda)(1-r_u) \theta_L [t_h \eta_{HL} (-c_{FP}) + (1-t_h) \eta_{LL} (-c_{FP}) - c_i] \\
+ \lambda r_u \theta_H t_u (1-\eta_{HH}) [f(\theta_H, \phi_{HH})] k + \lambda r_u \theta_H (1-t_u)(1-\eta_{HL}) [f(\theta_H, \phi_{HL})] k \\
+ \lambda (1-r_u) \theta_L t_u (1-\eta_{HL}) [f(\theta_L, \phi_{HL})] k.
\]

(5)

The first (second) line of the above expression represents the expected utility when the patient is unhealthy and the risk signal is high (low). Similarly, the third (fourth) line of the above expression represents the expected utility when the patient is healthy and the risk signal is high (low). The remaining represents the patient’s expected utility from the litigation.

Regarding the physician’s utility, we breach the notation and simplify the expression, \(E[U^{PH}(\eta_{s_r,s_t}|s_r,s_t,\theta_{s_r,\phi_{s_t}})]\), as \(E[U^{PH}|s_r,s_t]\). The respective utilities are given by

\[
E[U^{PH}|H,H] = u(1-\alpha) + \eta_{HH} ((1 - Pr[i = u|H,H])(-c_{FP}) - Pr[i = u|H,H] d(1-\mu)) \\
+ (1-\eta_{HH}) Pr[i = u|H,H][(-d + k f(\theta_H, \phi_{HH})) \alpha] \\
+ (1-\eta_{HH}) Pr[i = u|H,H][l - k(1 - f(\theta_H, \phi_{HH}))][(1-\alpha)],
\]

(6)

\[
E[U^{PH}|L,H] = u(1-\alpha) + \eta_{HL} ((1 - Pr[i = u|L,H])(-c_{FP}) - Pr[i = u|L,H] d(1-\mu)) \\
+ (1-\eta_{HL}) Pr[i = u|L,H][(-d + k f(\theta_L, \phi_{HL})) \alpha] \\
+ (1-\eta_{HL}) Pr[i = u|L,H][l - k(1 - f(\theta_L, \phi_{HL}))][(1-\alpha)],
\]

(7)

\[
E[U^{PH}|H,L] = u(1-\alpha) + \eta_{HL} ((1 - Pr[i = u|H,L])(-c_{FP}) - Pr[i = u|H,L] d(1-\mu)) \\
+ (1-\eta_{HL}) Pr[i = u|H,L][(-d + k f(\theta_H, \phi_{HL})) \alpha] \\
+ (1-\eta_{HL}) Pr[i = u|H,L][l - k(1 - f(\theta_L, \phi_{HL}))][(1-\alpha)],
\]

(8)

\[
E[U^{PH}|L,L] = u(1-\alpha) + \eta_{LL} ((1 - Pr[i = u|L,L])(-c_{FP}) - Pr[i = u|L,L] d(1-\mu)) \\
+ (1-\eta_{LL}) Pr[i = u|L,L][(-d + k f(\theta_L, \phi_{LL})) \alpha] \\
+ (1-\eta_{LL}) Pr[i = u|L,L][l - k(1 - f(\theta_L, \phi_{LL}))][(1-\alpha)],
\]

(9)

where \(Pr[i = u|s_r,s_t] \forall s_r,s_t \in \{H,L\}\) are the physician’s posterior probabilities defined as

\[
Pr[i = u|H,H] = \frac{\lambda r_u t_u}{(1-\lambda) r_h t_h + \lambda r_u t_u},
\]

(10)

\[
Pr[i = u|L,L] = \frac{\lambda (1-r_u) t_u}{(1-\lambda)(1-r_h) t_h + \lambda (1-r_u) t_u},
\]

(11)

\[
Pr[i = u|H,L] = \frac{\lambda r_u (1-t_u)}{(1-\lambda) r_h (1-t_h) + \lambda r_u (1-t_u)},
\]

(12)

\[
Pr[i = u|L,L] = \frac{\lambda (1-r_u)(1-t_u)}{(1-\lambda)(1-r_h)(1-t_h) + \lambda (1-r_u)(1-t_u)}.
\]

(13)
The social planner’s expected utility is given by

\[ E[U^{SP}] = \lambda r_u \theta_H [t_u \eta_{HL} d \mu + (1 - t_u) \eta_{LL} d \mu + u - d - c_l] + \lambda r_u (1 - \theta_H) (-d) \\
+ \lambda (1 - r_u) \theta_L [t_u \eta_{HL} d \mu + (1 - t_u) \eta_{LL} d \mu + u - d - c_l] + \lambda (1 - r_u) (1 - \theta_L) (-d) \\
+ (1 - \lambda) r_H \theta_H [t_h \eta_{HH} (-c_F P) + (1 - t_h) \eta_{H L} (-c_F P) + u - c_l] \\
+ (1 - \lambda) (1 - r_h) \theta_L [t_h \eta_{HH} (-c_F P) + (1 - t_h) \eta_{H L} (-c_F P) + u - c_l] \\
- \lambda r_u \theta_H t_u (1 - \eta_{HH} l) - \lambda r_u \theta_H (1 - t_u) (1 - \eta_{LL} l) - \lambda (1 - r_u) \theta_L t_u (1 - \eta_{LL} l). \tag{14} \]

The interpretation of the expected social welfare is similar to that of the patient’s expected utility. Note that, if litigation is not a concern, the patient’s expected utility, the physician’s expected utility, and the expected social welfare are similarly defined by letting \( l = 0 \) and \( k = 0 \).

**Proof of Lemma 1.**

Observe that the expected social welfare is a linear function in \( \eta_{s_r,s_l} \) for \( \forall s_r, s_l \in \{H, L\} \). This implies that the social planner sets \( \eta_{s_r,s_l} = 1 \) if

\[ \frac{\partial U^{SP}}{\partial \eta_{s_r,s_l}} \geq 0, \forall s_r, s_l \in \{H, L\}, \tag{15} \]

which can be reduced to

\[ \mu \geq \frac{(1 - \lambda) r_h t_h c_{FP}}{\lambda r_u t_h d} := T^{HH} \quad \text{for } s_r = H \text{ and } s_l = H, \tag{16} \]

\[ \mu \geq \frac{(1 - \lambda) (1 - r_h) t_h c_{FP}}{\lambda (1 - r_u) t_h d} := T^{LL} \quad \text{for } s_r = L \text{ and } s_l = H, \tag{17} \]

\[ \mu \geq \frac{(1 - \lambda) r_h (1 - t_h) c_{FP}}{\lambda r_u (1 - t_u) d} := T^{HL} \quad \text{for } s_r = H \text{ and } s_l = L, \tag{18} \]

\[ \mu \geq \frac{(1 - \lambda) (1 - r_h) (1 - t_h) c_{FP}}{\lambda (1 - r_u) (1 - t_u) d} := T^{HH} \quad \text{for } s_r = L \text{ and } s_l = L. \tag{19} \]

Otherwise, the social planner sets \( \eta_{s_r,s_l} = 0 \).

Recall that \( r_u > r_h, t_u > t_h, t_u > r_u, \) and \( t_h < r_h \). This implies

\[ \frac{r_h t_h}{r_u t_u} < \frac{(1 - r_h) t_h}{(1 - t_u) t_u} < \frac{r_h (1 - t_h)}{(1 - t_u) t_u} < \frac{(1 - r_h) (1 - t_h)}{(1 - t_u) (1 - t_u)}. \tag{20} \]

It follows that \( T^{HH} < T^{HL} < T^{HL} < T^{LL} \).  \( \text{Q.E.D.} \)

**Proof of Proposition 1.**

Observe that the expected social welfare is a linear function in \( \theta_{s_r} \) for \( \forall s_r \in \{H, L\} \).

(1) For \( \mu \leq T^{HH} \), \( \eta_{s_r,s_l} = 0, \forall s_r, s_l \in \{H, L\} \) by Lemma 1. Define \( U^{SP} := U^{SP}_{\eta_{HH} = \eta_{HL} = \eta_{LL} = 0} \). The social planner sets \( \theta_{s_r} = 1 \) if

\[ \frac{\partial U^{SP}}{\partial \theta_{s_r}} \geq 0 \Rightarrow c_l \leq u := S^H_0 = S^L_0, \forall s_r \in \{H, L\}. \tag{21} \]

However, this fails to hold by definition, \( c_l > u \) (i.e., the physician payment is a fraction of the testing cost), which implies \( \theta_{s_r} = 0 \) for \( \forall s_r \in \{H, L\} \).
For $T^{HH} \leq \mu \leq T^{LL}$, $\eta_{HH} = 1$ and $\eta_{HL} = \eta_{HL} = \eta_{LL} = 0$ by Lemma 1. Define $U^{SP}: = U^{SP} |_{\eta_{HH} = \eta_{HL} = \eta_{HL} = \eta_{LL} = 0}$. For $s_r = H$, the social planner sets $\theta_H = 1$ if

$$\frac{\partial U^{SP}}{\partial \theta_H} = 0 \rightarrow c_t \leq u - \frac{(1 - \lambda)(1 - r_h) c_{FP}}{(1 - \lambda)(1 - r_h) + \lambda (1 - r_u)} : = S^H_1 \tag{22}$$

The social planner sets $\theta_H = 0$ if $c_t \geq S^H_1$. For $s_r = L$, the result from part (1) holds.

For $T^{LL} \leq \mu \leq T^{HH}$, $\eta_{HH} = \eta_{HL} = \eta_{HL} = 1$ and $\eta_{LL} = 0$ by Lemma 1. Define $U^{SP}: = U^{SP} |_{\eta_{HH} = \eta_{HL} = \eta_{HL} = \eta_{LL} = 0}$. For $s_r = H$, the result from part (2) remains to hold. For $s_r = L$, the social planner sets $\theta_L = 1$ if

$$\frac{\partial U^{SP}}{\partial \theta_L} = 0 \rightarrow c_t \leq u - \frac{(1 - \lambda)(1 - r_h) c_{FP}}{(1 - \lambda)(1 - r_h) + \lambda (1 - r_u)} + \frac{\lambda r_u \mu d}{\lambda r_u + (1 - \lambda) r_h} : = S^L_1 \tag{23}$$

The social planner sets $\theta_L = 0$ if $c_t \geq S^L_1$. For $s_r = L$, the result from part (3) holds.

For $T^{LL} \leq \mu \leq T^{HH}$, $\eta_{HH} = \eta_{HL} = \eta_{HL} = 1$ and $\eta_{LL} = 0$ by Lemma 1. Define $U^{SP}: = U^{SP} |_{\eta_{HH} = \eta_{HL} = \eta_{HL} = \eta_{LL} = 1}$. For $s_r = H$, the result from part (4) remains to hold. For $s_r = L$, the social planner sets $\theta_L = 1$ if

$$\frac{\partial U^{SP}}{\partial \theta_L, \partial c_t} = 0 \rightarrow c_t = u - \frac{(1 - \lambda)(1 - r_h) c_{FP}}{(1 - \lambda)(1 - r_h) + \lambda (1 - r_u)} + \frac{\lambda (1 - r_u) c_{FP}}{(1 - \lambda)(1 - r_h) + \lambda (1 - r_u)} : = S^L_1 \tag{25}$$

The social planner sets $\theta_L = 0$ if $c_t \geq S^L_1$. Q.E.D.

**Proof of Proposition 2.**

We compute the physician’s expected utilities $E[U^{PH} | s_r, s_t]$ under the no litigation case as follows.

$$E[U^{PH} | H, H] = u(1 - \alpha) + \eta_{HH}((1 - Pr[i = u | H, H])(-c_{FP}) - Pr[i = u | H, H]d(1 - \mu)) + (1 - \eta_{HH})Pr[i = u | H, H](-d)\alpha,$$  \(E[U^{PH} | L, H] = u(1 - \alpha) + \eta_{HL}((1 - Pr[i = u | L, H])(-c_{FP}) - Pr[i = u | L, H]d(1 - \mu)) + (1 - \eta_{HL})Pr[i = u | L, H](-d)\alpha,$$  \(E[U^{PH} | H, L] = u(1 - \alpha) + \eta_{HL}((1 - Pr[i = u | H, L])(-c_{FP}) - Pr[i = u | H, L]d(1 - \mu)) + (1 - \eta_{HL})Pr[i = u | H, L](-d)\alpha,$$  \(E[U^{PH} | L, L] = u(1 - \alpha) + \eta_{LL}((1 - Pr[i = u | L, L])(-c_{FP}) - Pr[i = u | L, L]d(1 - \mu)) + (1 - \eta_{LL})Pr[i = u | L, L](-d)\alpha.$$

Note that each of the physician’s expected utility is linear in $\eta_{s_r s_t}$ for $\forall s_r, s_t \in \{H, L\}$. Thus, the physicians sets $\eta_{s_r s_t} = 1$ if

$$\frac{\partial E[U^{PH} | s_r, s_t]}{\partial \eta_{s_r s_t}} \geq 0, \forall s_r, s_t \in \{H, L\}, \tag{30}$$
The physician provides a recommendation if and only if
\[
\frac{\partial E[U^{PH}\mid{s_r,s_t}}]{\partial \eta_{s_r,s_t}} < 0, \forall s_r,s_t \in \{H,L\}.
\] (31)
These results give the same thresholds \(T^{s_r,s_t} \forall s_r,s_t \in \{H,L\}\) as defined in (16)–(19), which implies that the social planner’s decision in Stage I would be equivalent to the first-best. \(\text{Q.E.D.}\)

**Proof of Proposition 3.**

In Stage II, when the physician cannot infer the risk information, the posterior probabilities are given as
\[
P_T[i = u\mid{s_t} = H, \theta_H, \theta_L] = \frac{\lambda t \alpha \theta_H - \theta_L + \theta_L}{(1-\lambda) r \alpha \theta_H - \theta_L + \theta_L} + \lambda \theta_H - \theta_L \right]
(32)
\[
P_T[i = u\mid{s_t} = L, \theta_H, \theta_L] = \frac{\lambda (1-\alpha) t \alpha \theta_H - \theta_L + \theta_L}{(1-\lambda) r \alpha \theta_H - \theta_L + \theta_L} + \lambda \theta_H - \theta_L \right]
(33)
We then define the physician’s expected utilities \(E[U^{PH}\mid{s_t}]\) as below.
\[
E[U^{PH}\mid{H}] = u(1-\alpha) + \eta_H (1-PR[i = u\mid{H, \theta_H, \theta_L}])(-c_{FP}) - PR[i = u\mid{H, \theta_H, \theta_L}]d(1-\mu)
\]
\[
+ (1-\eta_H) (PR[i = u\mid{H, \theta_H, \theta_L}])(d+kf(\phi_H)) \alpha
\]
\[
+ [(1-\eta_H) (PR[i = u\mid{H, \theta_H, \theta_L}])(1-\lambda) kf(\phi_H)) / (1-\alpha),
\]
\[
E[U^{PH}\mid{L}] = u(1-\alpha) + \eta_L (1-PR[i = u\mid{L, \theta_H, \theta_L}])(-c_{FP}) - PR[i = u\mid{L, \theta_H, \theta_L}]d(1-\mu)
\]
\[
+ (1-\eta_L) (PR[i = u\mid{L, \theta_H, \theta_L}])(d) \alpha
\]
(35)
The physician provides a recommendation if and only if
\[
\frac{\partial E[U^{PH}\mid{s_t}}]{\partial \eta_{s_r}} \geq 0, \forall s_t \in \{H,L\}.
\] (36)
Observe that if \(\theta_H \geq \theta_L\), then condition (36) gives the following thresholds.
\[
\frac{\lambda t \alpha \theta_H - \theta_L + \theta_L}{(1-\alpha) t \alpha \theta_H - \theta_L + \theta_L} + \alpha(1-\lambda) (1-\alpha)(1-\lambda) kf(\phi_H) = T^{HH},
\]
\[
\frac{\lambda (1-\alpha) t \alpha \theta_H - \theta_L + \theta_L}{(1-\alpha) t \alpha \theta_H - \theta_L + \theta_L} + \alpha(1-\lambda) (1-\alpha) kf(\phi_H) = T^{HL},
\]
\[
\frac{\lambda t \alpha \theta_H - \theta_L + \theta_L}{(1-\alpha) t \alpha \theta_H - \theta_L + \theta_L} + \alpha(1-\lambda) (1-\alpha) kf(\phi_H) = T^{LL}.
\] (37)
We notice that
\[
T^{HH} \leq T^{HL} \leq T^{LH} \leq T^{LL}.
\] (39)
We also notice that
\[
\frac{\partial T^{s_r}}{\partial \theta_H} < 0, \frac{\partial T^{s_r}}{\partial \theta_L} > 0 \forall s_r \in \{H,L\}.
\] (40)
If \(\mu \geq T^{s_r}\), the physician sets \(\eta_{s_t} = 1 \forall s_t \in \{H,L\}\). If \(\mu < T^{s_r}\), the physician sets \(\eta_{s_t} = 0 \forall s_t \in \{H,L\}\).

In Stage 1, let \(\theta_H = 1\) and \(\theta_L = 0\). Then, we have \(T^{HH}\mid{\theta_H = 1, \theta_L = 0} \leq T^{HH}\) and \(T^{LL}\mid{\theta_H = 1, \theta_L = 0} = T^{HH}\). The physician’s decisions are identical to those under the first-best scenario. Therefore, the social planner can induce the first-best by choosing \(\theta_H = 1\) and \(\theta_L = 0\).
\(\text{Q.E.D.}\)
Proof of Lemma 2.

The physician sets \( \eta_{s_r,s_t} = 1 \) for \((s_r,s_t) \in \{(HH),(LH),(HL)\} \) if
\[
\frac{\partial E[U^{SP}]_s}{\partial \eta_{s_r,s_t}} \geq 0 \rightarrow \mu \geq \widetilde{T}^{s_r,s_t}, \forall (s_r,s_t) \in \{(HH),(LH),(HL)\}. \tag{41}
\]

The physician sets \( \eta_{s_r,s_t} = 0 \) if \( \mu < \widetilde{T}^{s_r,s_t} \), \( \forall (s_r,s_t) \in \{(HH),(LH),(HL)\} \). Note that the threshold for \((s_r,s_t) = (LL)\) is the same as \( T^{LL} \) since no litigation occurs for \((s_r,s_t) = (LL)\), and hence \( \eta_{LL} = 0 \) by Assumption 1. Also notice that \( \widetilde{T}^{HH} < T^{HH} \), which implies \( \eta_{HH} = 1 \). Q.E.D.

Proof of Proposition 4.

We derive the equilibrium under different conditions on the parameters, \( \mu \) and \( c_t \). Notice that the expected social welfare is linear in \( \theta_{s_r} \) for \( \forall s_r \in \{H,L\} \).

1. \( s_r = L \)

In Stage II, the physician sets \( (\eta_{HH} = 1, \eta_{LL} = 0) \) if \( \mu \geq \widetilde{T}^{LL} \) and sets \( (\eta_{HH} = 0, \eta_{LL} = 0) \) if \( \mu \leq \widetilde{T}^{LL} \) by Lemma 2. Let us define \( U^{SP} \) as the social planner’s utility \( U^{SP} \) evaluated at \( (\eta_{HH} = \eta_{LL} = 0) \) or \( (\eta_{HH} = 1, \eta_{LL} = 0) \). In Stage I, the social planner screens the patient if and only if
\[
\frac{\partial U^{SP}}{\partial \theta} \geq 0. \tag{42}
\]

But, this condition always fails to hold, which implies \( \theta_L = 0 \) and no-follow-up guideline (\( \phi_{HH} \) and \( \phi_{LL} \) do not exist).

2. \( s_r = H \)

In Stage II, the physician sets \( (\eta_{HH} = 1, \eta_{HL} = 1) \) if \( \mu > \widetilde{T}^{HL} \) and sets \( (\eta_{HH} = 1, \eta_{HL} = 0) \) if \( \mu \leq \widetilde{T}^{HL} \) by Lemma 2. Let us define
\[
\tilde{T}_1 := \widetilde{T}^{HL}(\theta_H, \phi_{HH})|_{\theta_H = 1, \phi_{HL} = 1} = T^{HL} - \frac{(1-2\alpha)k(a_{HL}+b_{HL})+(1-\alpha)l}{\alpha d},
\]
\[
\tilde{T}_2 := \widetilde{T}^{HL}(\theta_H, \phi_{HL})|_{\theta_H = 1, \phi_{HL} = 0} = T^{HL} - \frac{(1-2\alpha)k(a_{HL})+(1-\alpha)l}{\alpha d},
\]
\[
\tilde{T}_3 := \widetilde{T}^{HL}(\theta_H, \phi_{HL})|_{\theta_H = 0, \phi_{HL} = 0} = T^{HL} - \frac{(1-\alpha)l}{\alpha d} \cdot S_1^H = S_1^H - \frac{\lambda r_u(1-t_u)}{\lambda r_u+(1-\lambda)r_h}l. \tag{43}
\]

Observe that \( \widetilde{T}^{HL} \) is monotonically decreasing in \( \theta_H \) and \( \phi_{HL} \).

(i) Suppose first \( \mu \leq \tilde{T}_1 \). In Stage II, the physician chooses \( \eta_{HH} = 1 \) and \( \eta_{HL} = 0 \) by Lemma 2. In Stage I, the social planner screens the patient by setting \( \theta_H = 1 \) if and only if
\[
\frac{\partial U^{SP}}{\partial \theta} \geq 0. \tag{44}
\]

or
\[
c_t \leq \frac{(1-\lambda)r_h t_b c_{FP}}{(1-\lambda)r_h + \lambda r_u} + \frac{\lambda r_u t_u \mu d}{\lambda r_u + (1-\lambda)r_h} - \frac{\lambda r_u(1-t_u)}{\lambda r_u+(1-\lambda)r_h} + u = \tilde{S}_1^H. \tag{45}
\]

When (44) holds, we notice that \( \phi_{HH} \) and \( \phi_{HL} \) can be any value between 0 to 1 since they do not affect the physician’s decision (i.e., \( \mu \leq \tilde{T}^{HL} \) for any \( \phi_{HH} \) and \( \phi_{HL} \)) and the social welfare. But, we choose the first-best follow-up guidelines (\( \phi_{HH} = 1 \) and \( \phi_{HL} = 0 \)) to break the tie. When (44) fails to hold (i.e., \( c_t \geq \tilde{S}_1^H \)), \( \theta_H = 0 \) and no-follow-up guideline exists (i.e., \( \phi_{HH} \) and \( \phi_{HL} \) do not exist).
Case 1: Let us first assume that \((\eta_{HH}, \eta_{HL}) = (1,0)\) or \((1,1)\) by choosing guidelines \((\theta_H, \phi_{HH}, \phi_{HL})\) as in Lemma 2.

Observe that
\[
\frac{\partial U^{SP}}{\partial \eta_{HH}} = 0 
\]
if and only if \(c_t \leq S^H_1\).

If \(c_t \leq S^H_1\), the social planner sets \(\theta_H\) as high as possible while inducing \((1,0)\) in Stage II. Since \(\phi_{HL}\) has no impact on the social welfare as long as \(\mu \leq \tilde{T}^{HL}\) holds, setting \(\theta_H = 1\), \(\phi_{HH} = 1\), and \(\phi_{HL} = 0\) maximizes the social welfare. We notice that any \(\phi_{HL} \in [0,1]\) can be optimal, but we choose one that is consistent with the first-best to break the tie. We also notice that any \(\phi_{HL} \in [0, \phi]\) where \(\phi\) is such that \(\mu = \tilde{T}^{HL}(\theta_H = 1, \phi_{HL} = \phi)\) can be optimal, but we choose one that is rigid to break the tie.

If \(c_t \geq S^H_1\), then \(\phi_{HL} = 0\) if \(c_t = 0\) is optimal and no follow-up guideline exists (i.e., \(\phi_{HH}\) and \(\phi_{HL}\) do not exist).

Case 2: Next, let us assume that \((\eta_{HH}, \eta_{HL}) = (1,1)\) (i.e., \(\tilde{T}^{HL} < \mu\)) is induced in Stage II at equilibrium.

Observe that
\[
\frac{\partial U^{SP}}{\partial \eta_{HH}} = 0 
\]
if and only if \(c_t \leq S^H_2\).

If \(c_t \leq S^H_2\), the social planner sets \(\theta_H\) as high as possible while inducing \((1,1)\) in Stage II. Since \(\phi_{HL}\) has no impact on the social welfare as long as \(\tilde{T}^{HL} \leq \mu\) holds, setting \(\theta_H = 1\), \(\phi_{HH} = 1\), and \(\phi_{HL} = 1\) maximizes the social welfare. We notice that any \(\phi_{HL} \in [0,1]\) can be optimal, but we choose one that is consistent with the first-best to break the tie. We also notice that any \(\phi_{HL} \in [\phi, 1]\) where \(\phi\) is such that \(\mu = \tilde{T}^{HL}(\theta_H = 1, \phi_{HL} = \phi)\) can be optimal, but we choose one that is consistent with the first-best to break the tie.

If \(c_t \geq S^H_2\), then \(\phi_{HL} = 0\) if \(c_t = 0\) is optimal and no follow-up guideline exists (i.e., \(\phi_{HH}\) and \(\phi_{HL}\) do not exist).

In summary, if \(c_t \geq S^H_1\) and \(c_t \leq S^H_2\), then \((\theta_H = 1, \phi_{HH} = 1, \phi_{HL} = 1)\) is optimal at equilibrium. If \(c_t \leq S^H_1\) and \(c_t \geq S^H_2\), then \((\theta_H = 1, \phi_{HH} = 1, \phi_{HL} = 0)\) is optimal at equilibrium. If \(c_t \leq S^H_1\) and \(c_t \leq S^H_2\), the social planner compares the utilities under the two choices. The social planner chooses \((1,1,0)\) if and only if
\[
U^{SP}|_{\eta_{HH}=1, \eta_{HL}=1, \eta_{HL}=0} \geq U^{SP}|_{\phi_{HH}=1, \phi_{HL}=1, \phi_{HL}=1}. 
\]

This is reduced to
\[
\mu \leq \frac{(1 - \lambda) r_h (1 - t_h) c_{FP}}{d \lambda r_u (1 - t_u)} - \frac{l}{d} 
\]
But, this always holds since
\[
\bar{T}_2 < \frac{(1 - \lambda) r_h (1 - t_h) c_{FP}}{d \lambda r_u (1 - t_u)} - \frac{l}{d}.
\]

Thus, if \(c_t \leq S^H_2\) and \(c_t \leq S^H_1\), then \((\theta_H = 1, \phi_{HH} = 1, \phi_{HL} = 0)\) is optimal in Stage I at equilibrium.

(iii) Next, suppose \(\bar{T}_2 \leq \mu \leq \bar{T}_3\). In Stage I, the social planner can induce \((\eta_{HH}, \eta_{HL})\) such that \((\eta_{HH}, \eta_{HL}) = (1,0)\) or \((1,1)\) by choosing guidelines \((\theta_H, \phi_{HH}, \phi_{HL})\) by Lemma 2.
Case 1: Let us first assume that \((\eta_{HH}, \eta_{HL}) = (1,0)\) (i.e., \(\mu = \tilde{T}_{HL}\)) is induced in Stage II at equilibrium. Define 

\[ U^{SP} := U^{SP} |_{\eta_{HH} = 1, \eta_{HL} = 0}. \]

Observe that 

\[ \frac{\partial U^{SP}}{\partial \theta_H} \geq 0 \text{ if and only if } c_t \leq S_1^H. \]

If \(c_t \leq S_1^H\), the social planner sets \(\theta_H\) as high as possible while inducing \((1,0)\) in Stage II. Note that \(\phi_{HH}\) has no impact on the social welfare as long as \(\mu = \tilde{T}_{HL}\) holds. Let us define \(\theta_i\) such that 

\[ \mu = \tilde{T}_{\theta_H = \theta_i, \phi_{HL} = 0}. \]

Thus, the social planner chooses \((\theta_H = \theta_i, \phi_{HH} = 1, \phi_{HL} = 0)\) to maximize the social welfare if \(c_t \leq S_i^H\). We notice that any \(\phi_{HH} \in [0,1]\) can be optimal, but we choose one that is consistent with the first-best to break the tie.

If \(c_t \geq S_i^H\), then \(\theta_H = 0\) is optimal and no follow-up guideline exists (i.e., \(\phi_{HH}\) and \(\phi_{HL}\) do not exist).

Case 2: Next, let us assume that \((\eta_{HH}, \eta_{HL}) = (1,1)\) (i.e., \(\tilde{T}_{HL} \leq \mu\)) is induced in Stage II at equilibrium. Observe that 

\[ \frac{\partial U^{SP}}{\partial \theta_H} \geq 0 \text{ if and only if } c_t \leq S_2^H. \]

If \(c_t \leq S_2^H\), the social planner sets \(\theta_H\) as high as possible while inducing \((1,1)\) in Stage II. Since \(\phi_{HH}\) has no impact on the social welfare as long as \(\tilde{T}_{HL} \leq \mu\) holds, setting \(\theta_H = 1, \phi_{HH} = 1\) and \(\phi_{HL} = 0\) maximizes the social welfare. We notice that any \(\phi_{HH} \in [0,1]\) for \(\forall s_t \in \{H,L\}\) can be optimal, but we choose one that is consistent with the first-best to break the tie.

If \(c_t \geq S_2^H\), then \(\theta_H = 0\) is optimal and no follow-up guideline exists (i.e., \(\phi_{HH}\) and \(\phi_{HL}\) do not exist).

In summary, if \(c_t \geq S_1^H\) and \(c_t \leq S_2^H\), then \((\theta_H = 1, \phi_{HH} = 1, \phi_{HL} = 0)\) is optimal at equilibrium. If \(c_t \leq S_1^H\) and \(c_t \geq S_2^H\), then \((\theta_H = \theta_i, \phi_{HH} = 1, \phi_{HL} = 0)\) is optimal at equilibrium. If \(c_t \leq S_2^H\) and \(c_t \leq S_1^H\) hold, the social planner compares the utilities under the two choices. The social planner chooses \((\theta_i, 1, 0)\) if and only if 

\[ U^{SP} |_{\eta_{HH} = 0, \eta_{HL} = 0} \geq U^{SP} |_{\eta_{HH} = 1, \eta_{HL} = 0}. \]

This is reduced to 

\[ \theta_i \geq \frac{(1-\lambda)r_h c_{FP} + ((1-\lambda)r_h + \lambda r_u)c_t - \lambda r_u d\mu - (\lambda r_u + (1-\lambda)r_h)u}{(1-\lambda)r_h t_h c_{FP} + ((1-\lambda)r_h + \lambda r_u)c_t + \lambda r_u t_h d\mu - (\lambda r_u + (1-\lambda)r_h)u + \lambda r_u (1-t_u)} := \tilde{\theta}_i. \]

(iv) Finally, suppose \(\tilde{T}_3 < \mu\). In Stage II, the physician always provides a follow-up (i.e., \(\eta_{HH} = 1\) and \(\eta_{HL} = 1\)) by Lemma 2. Therefore, the social planner sets \(\theta_H = 1\) if and only if 

\[ c_t \leq S_2^H. \]

Therefore, if \(c_t \leq S_2^H\), then \((\theta_H = 1, \phi_{HH} = 1, \phi_{HL} = 0)\) is optimal at equilibrium. If \(c_t > S_2^H\), then \((\theta_H = 0, - , - )\) is optimal in Stage I at equilibrium. Q.E.D.
**Proof of Proposition 5.**

The results can be obtained by taking partial derivatives of \( \theta_i \) with respect to \( r_u, r_h, t_u, \) and \( t_h \). Observe that

\[
\frac{\partial \theta_i}{\partial r_u} = \frac{\alpha(1-\lambda)r_h(1-t_u)_{CP}}{(1-2\alpha)k\lambda a_{HL}r_u^2(1-t_u)} < 0, \tag{57}
\]

\[
\frac{\partial \theta_i}{\partial r_h} = \frac{\alpha(1-\lambda)(1-t_h)_{CP}}{(1-2\alpha)k\lambda a_{HL}r_u(1-t_u)} > 0, \tag{58}
\]

\[
\frac{\partial \theta_i}{\partial t_u} = \frac{(1-2\alpha)k\lambda a_{HL}r_u(1-t_u)^2 > 0, \tag{59}
\]

\[
\frac{\partial \theta_i}{\partial t_h} = \frac{\alpha(1-\lambda)_{CP}r_h}{(1-2\alpha)k\lambda a_{HL}r_u(1-t_u)} < 0, \tag{60}
\]

which gives the results. Q.E.D.

**Proof of Proposition 6.**

Part (1) can be obtained by taking partial derivatives of \( \bar{T}^{HL}(\theta_{H,\phi_{HL}}) \) with respect to \( \alpha \). Part (2) can be obtained by taking partial derivatives of \( \theta_i \) with respect to \( \alpha \). Observe that

\[
\frac{\partial e_T^{HL}}{\partial \alpha} = \frac{k_{HL} + l}{\alpha^2 d}, \tag{61}
\]

\[
\frac{\partial \theta_i}{\partial \alpha} = -\frac{(1-\lambda)r_h(1-t_h)_{CP} - \lambda r_u(1-t_u)(d\mu + l)}{(1-2\alpha)^2 k\lambda a_{HL}r_u(1-t_u)}. \tag{62}
\]

\( \frac{\partial e_T^{HL}}{\partial \alpha} \) is trivially positive by definition. \( \frac{\partial \theta_i}{\partial \alpha} \) is positive if and only if

\[
\mu < \left(\frac{1-\lambda}{d\lambda r_u(1-t_u)}\right) + \frac{l}{d}, \tag{63}
\]

which is true since

\[
\mu = \bar{T}^{HL}(\theta_i,0) < \left(\frac{1-\lambda}{d\lambda r_u(1-t_u)}\right) - \frac{l}{d}. \tag{64}
\]

Q.E.D.

**Proof of Proposition 7.**

Similar to Proposition 4, we derive the equilibrium under different conditions on the parameters. If \( k(a_{HL} + b_{HL}) \leq \bar{k} \), then the model is reduced to the baseline model with the litigation concern. Thus, we only consider the case where \( k(a_{HL} + b_{HL}) > \bar{k} \).

1. \( s_r = L \)
   
   As in the baseline model, the social planner does not screen the patient and we obtain the same result.

2. \( s_r = H \)
   
   In Stage II, the physician recommends the patient a follow-up if and only if

   \[
   \frac{\partial E[U^{FH}|H,s_t]}{\partial \eta_{H,s_t}} \geq 0, \forall s_t \in \{ H, L \} \tag{65}
   \]

   These conditions can be reduced to

   \[
   \mu \geq \bar{T}^{HH} - \frac{(1-\alpha)l + (1-2\alpha)\min[kf(\theta_H,\phi_{HL,H}),\bar{k}]}{\alpha d}, \text{ for } s_t = H, \tag{66}
   \]

   \[
   \mu \geq \bar{T}^{HL} - \frac{(1-\alpha)l + (1-2\alpha)\min[kf(\theta_L,\phi_{HL,L}),\bar{k}]}{\alpha d} := \bar{T}^{HL}, \text{ for } s_t = L. \tag{67}
   \]
But, condition (66) always holds by Assumption 1. Thus, \( \eta_{HH} = 1 \) while \( \eta_{HL} \) can be either one or zero depending on value of \( \mu \) compared to \( T^{HL} \). Let us define

\[
T_1 = T|_{\phi_H = 1, \phi_L = 1} \quad T_2 = T|_{\phi_H = 1, \phi_L = 0} \quad T_3 = T|_{\phi_H = 0, \phi_L = 0} = \overline{T}_3. \tag{68}
\]

The remaining analysis is analogous to that of the baseline litigation model but with the different thresholds defined in (68). Q.E.D.