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NEGLIGENCE AND TWO-SIDED CAUSATION

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Abstract: We extend the economic analysis of negligence and intervening causation to "two-sided causation" scenarios. In the two-sided causation scenario the effectiveness of the injurer's care depends on some intervention, and the risk of harm generated by the injurer's failure to take care depends on some other intervention. We find that the distortion from socially optimal care is more severe in the two-sided causation scenario than in the one-sided causation scenario, and generally in the direction of excessive care. The practical lesson is that the likelihood that injurers will have optimal care incentives under the negligence test in the presence of intervening causal factors is low.

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Tort cases that examine causation have a common factual structure. First, the injurer fails to take care. Second, some intervening act or omission occurs. The presence or absence of the intervening act alters the risk associated with the injurer's failure to take care. Third, the victim is injured.

This paper presents a core model of the causation problem and uses it to explore incentives for care in a rich set of causation scenarios. In the core model, the impact of the injurer's care on the probability of an injury depends on an intervention that determines whether care will be effective. Many negligence cases fall within this model; perhaps the most famous is *New York Central R.R. v. Grimstad*.[1] In *Grimstad* the plaintiff's decedent, captain of a covered barge, drowned after falling off the barge when it was bumped by a tugboat while lying in port. The captain's wife, with him at the time of the accident, brought suit on the theory that the barge owner was negligent in failing to install lifebuoys. If lifebuoys had been on the barge, according to the wife, she would have been able to grab one and throw it in time to save the captain. The appellate court held that although the barge owner was negligent in failing to equip the barge with lifebuoys, there was no evidence that the captain's wife would have been able to find a lifebuoy and throw it in time. Since the captain's drowning probably would have occurred even if the barge had been equipped with lifebuoys, the plaintiff lost her negligence lawsuit, on causation grounds.

This one-sided intervening causation scenario, in which the defendant's care depends on an intervention that determines whether care will be effective, is common in the negligence cases, and has been examined from an economic perspective in Shavell (1980), Landes & Posner (1983), Grady (1983), Kahan (1989), Marks (1994), and Hylton & Lin (2013). The Shavell, Landes & Posner, Grady, Kahan, and Marks papers assume that courts have full information. Hylton and Lin assume courts have limited information, in the sense of not knowing the distribution of the probability of intervention.

If courts have full information, injurers will exercise optimal care under the negligence test in the presence of intervening causation; assuming no judicial error and zero litigation costs.[2] If, on the contrary, courts have limited information, injurers may not exercise optimal care. Since the limited information setting is likely to be common, the interesting question is finding the direction and magnitude of the distortion from optimal care, under conditions that reflect the actual decision processes of courts in causation cases.

The problem of limited information in causation analysis was first addressed by Calabresi (1975), who suggested that courts, constrained by lack of information and by evidence

[1] 264 F. 334 (2d Cir. 1920).

[2] Grady (1983), Kahan (1989). If there is a risk of judicial error (given a fully informed court), then actors may take too much care in the full information model if courts do not apply the causation test correctly; but if courts apply the test correctly, care incentives will be optimal (Grady, 1983). For a recent survey, see Grady (2013).

norms, essentially perform an *ex post* evaluation of negligence in intervening causation cases, using information revealed by the accident.[3] We examine the distortive potential – that is, the extent to which care deviates from the socially optimal level – of the *ex post* negligence assessment here.

More specifically, we extend the one-sided causation analysis in Hylton & Lin (2013) to the two-sided causation scenario. In the two-sided causation scenario the effectiveness of the injurer's care depends on some intervention, as in *Grimstad*. However, in addition to this, the risk of harm generated by the injurer's failure to take care depends on some other intervention. Like the one-sided causation scenario, the two-sided causation scenario is common in the negligence case law.

The two-sided causation scenario presents a potentially interesting problem for several reasons. First, from the perspective of tort doctrine, the possibility of intervention altering the effectiveness of the injurer's care is treated as a "factual causation" issue, and the possibility of intervention altering the risk associated with the injurer's failure to take care is discussed as a "proximate causation" issue. This model examines the incentive effects of tort law in the presence of combined factual and proximate causation issues. Second, although care is generally distorted from optimality in the one-sided causation scenario, an optimal care outcome still remains possible, and is plausible in that scenario for many negligence settings.[4] The question this raises is whether optimal care is still a plausible outcome in the two-sided scenario.

To elaborate, Hylton & Lin found a tendency toward excessive care in the one-sided causation scenario. If the tendency is compounded in the two-sided causation scenario, as seems likely, how bad is the resulting distortion? Does the compounded distortion suggest that optimal or inadequate care outcomes are unlikely? These questions are addressed here.

We develop a measure of the extent to which care is distorted from the optimal level under the negligence test in the presence of intervening causal factors. We find that in the two-sided causation scenario, the distortions from optimal care are considerably more severe than in the one-sided causation scenario. The direction of the distortion depends on the distributions of both of the relevant intervention probabilities. Using simulations incorporating assumptions we consider representative of negligence cases, we find that the general distortion is toward excessive care. More importantly, the simulations suggest that the compounding of distortions is so great that the optimal care and inadequate care outcomes are unlikely in the two-sided scenario.

In our simulations, we use the Beta distribution for the intervention probabilities because it permits us to simulate a wide range of probability distributions for the intervention probabilities – from symmetrical to strongly skewed. The different parameters of the model permit us to simulate a wide event space of outcomes under the negligence test. We find that the parameter assumptions (specifically, regarding the productivity of

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[3] On the *ex post* nature of causation analysis, see also Wright (1985), Landes & Posner (1987).
[4] Hylton & Lin (2013).

precaution) required to generate optimal or inadequate care outcomes in the two-sided causation scenario are so narrow that these outcomes appear to be implausible. We also find that there is a possible solution: under a proportionate damages measure, as suggested in Shavell (1985), the optimal care outcome is considerably more plausible.[5]

The practical lesson of this paper is that the likelihood that injurers will have optimal care incentives under the negligence test in the presence of intervening causal factors affecting both care and risk appears to be low. The model developed here provides a more fine-grained analysis of the relationship between causation and the incentive for care than under standard models that assume full information courts.[6] The model could be applied to analyze incentives in real world settings in which probability distributions can be assigned to causal interventions. Moreover, the model could be applied to more general settings in law enforcement where causation issues arise.

Part II presents several examples of causation scenarios reflected in the negligence case law, and uses a numerical example to illustrate our core argument. Part III presents the model and our method of measuring the distortion from optimal care. Part III also presents conditions under which care is optimal, excessive, or inadequate under the negligence test, and simulations of the model. Part IV concludes.

II. Two-Sided Causation Scenarios: Examples

Given the ubiquity of intervening causal factors, every negligence dispute could be viewed as a two-sided causation case, depending on the granularity with which one identifies intervening factors. Even in the simple automobile accident, the effectiveness of care in maintaining, say, a braking system depends on the attentiveness of the driver (an intervening factor on the care side), and the dangerousness of failing to take care depends on the presence of potential victims (an intervening factor on the harm side).

But courts do not view every negligence case as a two-sided causation problem. The causation question arises only in cases where the facts raise a substantial question whether the actor should be considered negligent in light of the low probability of a particular intervention occurring. Here are some examples that illustrate the sorts of cases in which the causation problem attracts attention.

A. Boat Safety Scenario

The first two-sided causation scenario we consider is a straightforward extension of the *Grimstad* facts. Recall that in *Grimstad*, the captain fell overboard after his barge was

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[5] To be precise, we find that the optimal care outcome is possible irrespective of the assumed value of the productivity of care.

[6] One can view the full information model as a special case of the limited information model. An intermediate case, which we do not consider here, would have the court knowing the distribution of the intervention probability for only one of two intervening factors. The approach used in this paper for measuring distortion from optimal care could be applied to intermediate versions.

bumped by a tugboat while it was anchored in port. The bump is itself an intervention that dramatically increased the risk of an injury.

In this new scenario there are two potential interventions that affect the productivity of taking care (i.e., installing lifebuoys). One intervention is on the care side: care is ineffective unless someone can get to a lifebuoy in time to save the drowning victim. The other intervention is on the risk side: failing to take care (failing to install lifebuoys) does not increase the risk of injury unless a tugboat bumps the barge.

To get a sense of the influence of causation assessments, consider the following illustration. The barge owner, who has decided not to install lifebuoys, knows how often the captain is likely to be alone (or with only his wife) instead of surrounded by experienced sailors. Also, the barge owner knows how likely it is that the barge will be bumped by a tugboat while lying in port.

The probability of intervention on the care side is the probability that a certain type of rescuer will be available (on one extreme, an experienced sailor, or, on the other extreme, the captain's wife). The expected probability of care-side intervention averages over the rescuer types. After the accident occurs, the court sees the specific rescuer and forms an estimate of the intervention probability for the event that materialized. Similarly, the expected probability of intervention, on the risk side, averages over the times when a tug is likely to bump the barge and the times when a tug is unlikely to do so. These events depend on the density of tugboat traffic. The expected probability of risk-side intervention averages over the relevant traffic densities.

Assume two probabilities of care-side intervention, ¼ and ¾. The low probability corresponds to the instances in which the captain is on the barge with only his wife, or alone, while the high probability corresponds to instances in which the captain is with other experienced sailors. The low intervention probability scenario occurs with frequency ¼ and the high intervention probability scenario occurs with frequency ¾. Thus, the expected probability of care-side intervention is $(\frac{1}{4})(\frac{1}{4}) + (\frac{3}{4})(\frac{3}{4}) = {}^{5}/_{8}$. The frequencies of the high-intervention and low-intervention probability scenarios are known to the barge owner but not to the court.

Similarly, let there be two probabilities of risk-side intervention, ¼ and ¾, where the low probability reflects the likelihood of a bump from a tug in low density periods (only one tug is present) and the high probability is the likelihood of a bump in high density periods (two tugs are present). Let the corresponding traffic density frequencies be ¼ and ¾. These probabilities are known to the barge owner but not to the court.

Finally, let the probability of injury be ¾ if the barge owner fails install lifebuoys and an accident occurs, and ¼ if the barge owner installs lifebuoys and the lifebuoys are effectively deployed. The cost of installing lifebuoys is $1,500, and the injury resulting from the captain's drowning is $10,000.

Under the standard "Hand Formula" approach, the barge owner should install lifebuoys if the cost of taking care is less than the expected loss avoided. To fail to do so under these conditions would constitute negligence. The expected loss avoided is simply the differential in injury probabilities multiplied by the average probabilities of intervention (on both the care side and the risk side):

$$(5/8)(5/8)(3/4 - 1/4)(\$10,000) = \$1,953.12$$

Since the cost of installing lifebuoys, $1,500, is less than $1,953.12, the barge owner is negligent in failing to do so.

After the accident occurs, and the lawsuit filed, the court reviews the accident evidence, and determines negligence based on actual (or realized) intervention probabilities.[7] Suppose the accident occurs in the low density period (only one tug is present) and when the captain is on the barge with only his wife. Based on the observed evidence, the expected loss avoided by installing lifebuoys is

$$(1/4)(1/4)(3/4 - 1/4)(\$10,000) = \$312.50$$

And since this is less than the cost of installing lifebuoys, the court concludes that the barge owner was not negligent.

The key behind the court's conclusion, legally valid and economically erroneous, is its *ex post* assessment of causal factors. On the care side, the court concludes that the likelihood of intervention preventing an injury (deployment of lifebuoys) is too low to have made a difference. On the risk side, the court concludes that the likelihood of an intervention leading to an injury (a bump by a tugboat) is too low, given the observed traffic density, to require heightened precaution.

B. Safe Lock Scenario I

Another two-sided causation scenario involves the decision to lock something that might be valuable to keep it out of the hands of thieves. Suppose, for example, a hotel or jewelry store has a choice whether to purchase a safe in which to store valuable items. For the safe to be effective against thieves, however, someone tending the safe has to lock it. In *Wallinga v. Johnson*,[8] the plaintiff left jewelry to be kept in a hotel safe, but the hotel employees failed to lock the safe. Thieves robbed the hotel and took the jewelry.

However, failing to lock a safe does not create a risk if thieves never attempt to steal. Thus, in this scenario there are two types of intervention that affect the productivity of

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[7] Unless the barge owner voluntarily reveals the expected intervention probabilities, the court has no way of determining them. From the court's perspective any testimony on these probabilities would be regarded as conjectural and speculative, since it cannot be tested and verified. The observed intervention probabilities, however, are verifiable and therefore acceptable as a basis for determining negligence.

[8] 131 N.W.2d 216 (Minn. 1964).

taking care (installing a safe): intervention on the care side (locking the safe), and intervention on the harm side (by thieves).

C. Safe Lock Scenario II

In the previous scenarios the risk of an intervention leading to injury was assumed not to depend on whether the actor took care. In Boat Safety Scenario, for example, the probability of a boat bumping the barge does not depend on whether the barge installed lifebuoys. In Safe Lock Scenario I, the probability that thieves would attempt to steal does not depend on whether a safe was present.

In many instances, taking care does affect the probability that a third party will intervene. Consider the risk of a car theft as a function of the safety measures taken by the car owner. If the owner is careless, and leaves his keys in a visible place in the car, then an intervening actor (thief) may open the car and drive off with it. On the other hand, if the owner is careful, taking his keys and locking his car door, it is still possible that a thief will steal the car. But the probability of car theft is clearly higher when the owner leaves the keys in the car. In *Ross v. Hartman*,[9] a thief, spotting the key in the ignition, stole the defendant's car and negligently ran over the plaintiff. The court found that the thief's conduct was proximately caused by the defendant's negligence.

In *Strong v. Granite Furniture Co*.,[10] the defendant's negligent failure to lock the window of the plaintiff's house allowed a burglar to enter. The court held that the burglar's damage was not proximately caused by the defendant's negligence. Leaving the windows open makes it easy for a burglar to enter. However, locking the windows does not foreclose the possibility of a burglary; it only reduces the probability.

There is only one intervening act (the theft) in the two examples just considered (*Ross* and *Strong*). Still, these are cases of two-sided causation, because the probability of third party intervention depends on whether the initial actor takes care.

It is easy to modify the previous scenarios (Boat Safety, Safe Lock I) to allow for the kind of interdependency observed here. In Safe Lock I, for the safe to be effective, the person tending the safe must remember to lock it. However, thieves might be less likely to attempt to steal when they are aware that a safe is present. The thieves might assume that the safe is locked, and decide to find some other hotel (diversion effect) where the owners do not use safes.[11]

II. Model

We start with a presentation of the standard one-sided causation scenario, and then move on to two-sided scenarios. First, we lay out the basic model and then develop a measure of the distortion from optimal care.

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[9] 138 F.2d 14 (D.C. Cir. 1943).
[10] 294 P. 303 (Utah 1930),
[11] On the diversion effect of precaution against theft, see Baumann & Friehe (2013).

A. One-Sided Causation

1. Core Model

Taking care affects the probability of an accident, but the effect is conditional on an intervention. Let r = the probability of an injury given that the injurer does not take care. Let s = the probability of an intervention that makes care effective, w = the probability of an injury if the intervention occurs, $w < r$. Let x = the cost of taking care, and let L = the loss suffered by the accident victim. Moreover, we assume we assume $x < (r - w)L$.

The causation problem described is captured in the following tree diagram.

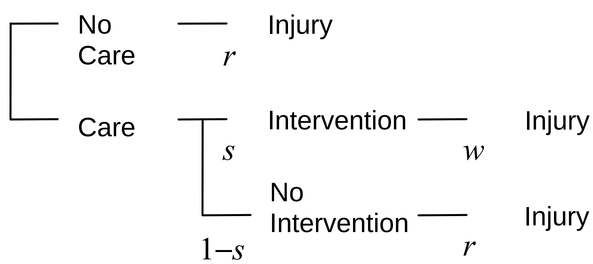

Figure 1: Causation event diagram

Before the injurer chooses how much care to take, the probability of intervention is unknown; only its distribution is known by the injurer. After the injurer invests in care, the actual intervention probability s_0 is revealed and an accident occurs. The injurer's care decision is a durable type of precaution that affects the probability of an accident once the intervention probability is realized later. The court cannot observe the distribution of the intervention probability, but the court does observe the actual intervention probability s_0 when it determines liability.

Let the intervention probability be governed by the distribution $G(s)$ with corresponding density $g(s)$. Taking care is socially desirable if the expected social cost when the injurer takes care is less than the expected social cost when the injurer does not take care, $x < (r - w)E(s)L$, where $E(s) = \int_0^1 sg(s)ds$ is the expected value of the intervention probability.

However, since the court has limited information it cannot apply the optimal care standard, $x < (r - w)E(s)L$, to determine negligence. Specifically, the court does not know $G(s)$ and therefore cannot determine $E(s)$.

In view of the court's limited information, we model the negligence determination in the presence of an intervening causal factor as an *ex post* assessment – an assessment based on the observation of the actual intervention probability.[12] There are two justifications for this approach.

First, this is what courts have done in the causation cases. The court's finding against causation in *Grimstad* was based on its *ex post* observation of the actual intervention probability, which was determined by the fact that the captain's wife was the only person on the barge at the time of the accident. The *ex post* assessment method is common in the causation cases.[13]

Second, the *ex post* approach is more or less required by accepted evidence and procedure constraints. Courts are required to use verifiable rather than speculative or conjectural evidence. This is a fundamental rule in many provisions of state and federal evidence law, and in civil jury instructions.[14] The observed intervention probability is verifiable, while the distribution of the intervention probability is a matter of speculation and conjecture for the (limited-information) court. Moreover, testimony from the informationally-advantaged defendant on the distribution of the intervention probability would also be non-verifiable, as well as biased by self-interest.

Under the *ex post* assessment of negligence, the injurer will be held liable if he fails to take care and, under the particular realization of the intervention probability, say s_0, care would have been socially beneficial, $x < (r - w)s_0L$, or $x/(r - w)L < s_0$. It follows that the injurer takes care under the negligence test when

$$x < [1 - G\left(\frac{x}{(r-w)L}\right)]rL \quad . \tag{1}$$

Hylton & Lin (2013) prove that in the one-sided intervening causation scenario, the *negligence test leads to socially excessive care if* $(r - w)E(s) < r[1 - G(E(s))]$, *socially*

[12] The notion that negligence is determined *ex post*, using information revealed by the accident, is noted in Calabresi (1975) and assumed in the early formalization of Landes & Posner (1983). The *ex ante* versus *ex post* problem is discussed briefly in Landes & Posner (1987, at 235), though informally and in response to criticisms of their work.

[13] Consider the following examples. In Gyerman v. United States Lines, 7 Cal. 3d 488, 498 P.2d 1043, 102 Cal. Rptr. 795 (1972), the defendant charged the plaintiff with contributory negligence for failing to inform his supervisor of a dangerous condition in the workplace. The evidence suggested that the accident probably would have happened even if the plaintiff had informed the supervisor. The court concluded that the defendant failed to show that the plaintiff's negligence was a substantial factor causing the injury. In Rouleau v. Butler, 152 Atl. 916 (N.H. 1931), involving an accident between the defendant's truck and the plaintiff, the defendant failed to signal his turn, but the plaintiff's driver was not looking for the signal over most of the time in which it might have made a difference. In City of Piqua v. Morris, 98 Ohio St. 42, 120 N.E. 300 (1918), the evidence suggested that the flood caused by an unusual rainfall was sufficient to account for the plaintiff's property loss, even if the defendant had taken the precautions urged by the plaintiff. In Weeks v. McNulty, 48 S.W. 809 (Tenn. 1898), the court found that a hotel was negligent for failing to install a fire escape, but there was insufficient evidence to indicate that the plaintiff's decedent would have used a fire escape.

[14] See, e.g., Vermont's general jury instructions, at http://www.vtbar.org/UserFiles/Files/WebPages/Attorney%20Resources/juryinstructions/civiljuryinstructions/generaljury.htm.

optimal care if equality holds, *and socially inadequate if the inequality is reversed*. The left side of the inequality, $(r - w)E(s)$, is the marginal social benefit of care (per dollar of loss L). The right side of the inequality, $r[1-G(E(s))]$, is the marginal private benefit of care (per dollar of loss) evaluated at the efficiency cut-off ($x = (r - w)E(s)L$). Thus, if the marginal private benefit of care, at the efficiency cut-off, exceeds the marginal social benefit of care, the incentive for care will be excessive.

One approach to measuring the incentive distortion is to examine the wedge between the marginal social benefit of care and the marginal private benefit of care at the efficiency cut-off. That measure is equal to: $L\{(r - w)E(s) - r[1-G(E(s))]\}$, which is negative in the case of a distortion toward excessive care and positive in the case of a distortion toward inadequate care. Letting D represent the distortion,

$$D = \varphi - \frac{(1 - G(E(s)))}{E(s)}, \qquad (2)$$

where $\varphi = (r - w)/r$, and measures the productivity of care.[15]

For comparison purposes we consider examples in which we calculate the relative size of the incentive distortion for a fixed value of the loss L. For these comparisons it is sufficient to look only at D.

For example, if the intervention probability follows the Exponential distribution,

$$E(s) = \int_0^1 \frac{\frac{s}{\lambda}}{1 - e^{\frac{-1}{\lambda}}} ds = \left(\frac{\lambda}{1 - e^{\frac{-1}{\lambda}}}\right)\left[1 - (1 + \frac{1}{\lambda})e^{\frac{-1}{\lambda}}\right]$$

$$G(E(s)) = \int_0^{E(s)} \frac{\frac{1}{\lambda}e^{\frac{-x}{\lambda}}}{1 - e^{\frac{-1}{\lambda}}} dx = \left(\frac{1}{1 - e^{\frac{-1}{\lambda}}}\right)\left[1 - e^{\frac{-E(s)}{\lambda}}\right]$$

$$D = \varphi - \frac{(1 - G(E(s)))}{E(s)} = \varphi - \frac{1 - e^{\frac{-E(s)}{\lambda}}}{\lambda[1 - (1 + \frac{1}{\lambda}e^{\frac{-1}{\lambda}})]}.$$

[15] Under a proportional damages measure $(r - w)L/r$, this distortion measure simplifies to a term proportional to $E(s) - (1 - G(E(s)))$, which is equal to zero for a symmetric distribution. However, for non-symmetric G, the distortion problem remains. Shavell (1985) proposes a proportional damages measure for causation cases. The proportional damages award also represents the setting where counterfactual damages are subtracted. Thus, subtracting counterfactual damages would not be sufficient to generate optimal care.

As φ goes from zero to one, care becomes more productive. The distribution parameter λ is equal to the expected value of the intervention probability. The optimal care curve consists of the parameter values (φ, λ) for which the distortion measure $D = 0$, which traces out a rectangular hyperbola.

2. Simulation 1: Beta Distribution

We allow for the intervention probability (signal) to have a Beta distribution. The advantage of the Beta is that it permits us to examine the incentives for care as the signal distribution changes from symmetrical to skewed.

Figure 2 shows the value of D as a function of the mean of the signal distribution ($\alpha/(\alpha+\beta)$). We used different values for the productivity of care φ, shown in the box in Figure 2. The distortion curve shifts up as the productivity of care increases. The dashed curve is associated with a value of φ of 2/3. The dotted curve is associated with a φ value of .89. The diamond-dotted curve is associated with a φ value of roughly .95. The solid black curve is associated with a φ value of .5.[16]

As we increase the mean of the Beta-distributed signal, we move from a signal distribution that is skewed left to one that is skewed right. The symmetrical distribution is represented by the midpoint along the horizontal axis, where $\alpha/(\alpha+\beta) = .5$.

In plotting the curves shown in Figure 2, we assumed $\alpha+\beta = 20$. In order to change the degree of skewness of the distribution, we moved the parameters, in one-digit increments, from the combination $\{\alpha = 1, \beta = 19\}$ to the combination $\{\alpha = 19, \beta = 1\}$, and plotted the distortion measure for each of the corresponding values of $\alpha/(\alpha+\beta)$. In other words, the values of $\alpha/(\alpha+\beta)$ begin at 1/20 and run up to 19/20.

Where the distortion variable is negative, the actor takes excessive care. Inadequate care is associated with positive distortion values. Optimal care is observed where the distortion value is equal to zero.

Figure 2 indicates a tendency toward excessive care under the negligence test. For most of the distribution patterns simulated the distortion measure is negative. This is somewhat counterintuitive if ones' first inclination is to think that the causation requirement reduces the scope of liability, and should therefore result in a weaker incentive for care.

The three highest curves in Figure 1 cross the zero distortion line, which means that there exists a set of Beta distribution parameter values, under the three highest assumed productivity of care levels ($\varphi = .67$, $\varphi = .89$, and $\varphi = .95$), for which care is socially optimal. The dashed curve, which graphs distortion levels for $\varphi = .67$, crosses the zero distortion line (optimal care) when the signal mean value ($\alpha/(\alpha+\beta)$) is roughly equal to .85. The dotted curve ($\varphi = .89$) crosses the zero line when the signal mean is .6. The

[16] We used $\varphi = (⅔ - ⅓)/(⅔) = .5$ for the solid black curve.

diamond-dotted curve (φ = .95) crosses the zero line when the signal mean is .55. The solid black curve (φ = .5) does not cross the zero distortion line.

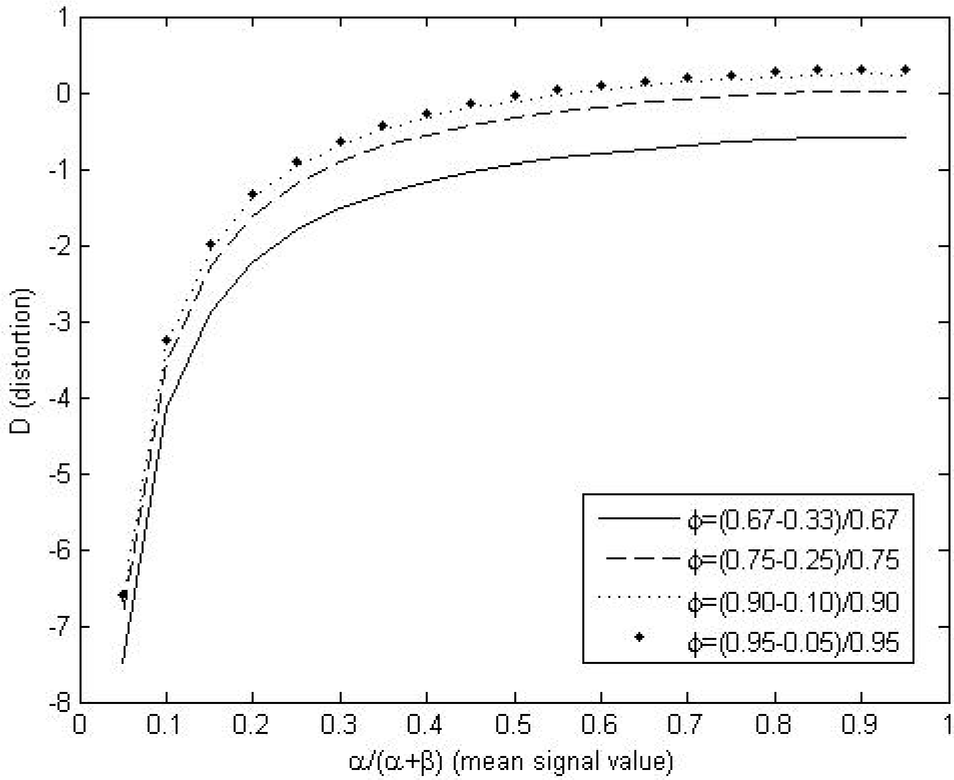

Figure 2: Distortion from Optimal Care, Beta Distribution Case

This simulation implies that in order to have an outcome in which care is socially optimal, rather than excessive, both the productivity of care and the signal mean have to have relatively high values. Specifically, for optimal care to be observed under the negligence test, the degree of the productivity of care must be above a certain threshold (specifically, $\varphi \geq .65$)[17] and the signal distribution must be sufficiently skewed to the right.

B. Two-Sided Causation

Here we model two-sided causation scenarios – again in the presence of limited-information courts. After examining some two-sided causation models, which are by no means exhaustive of the types of cases in which the two-sided causation problem might arise, we examine simulations. We compare the results of the one-sided model

[17] We ran several simulations for different values of the productivity of care (φ), and found that the productivity value must be greater than or equal to .65 in order to observe an outcome in which care is optimal (D = 0).

simulations to those of the two-sided model simulations in order to determine whether the degree of distortion from optimal care is greater in the two-sided scenario. We find that the distortion is greater.

1. Independent Interventions

The first set of two-sided causation scenarios we consider involves independent interventions – that is, scenarios where intervention on the care side is independent of the probability of intervention on the risk side. For ease of comparison with previous results, we start with an extension of the Boat Safety Scenario examined in the preceding section of this paper.

a. Boat Safety Scenario

Continuing with the scenario based on *Grimstad*, suppose the risk of injury depends on the conduct of an intervening actor. Specifically, suppose that the risk of drowning increases substantially *only* if the captain's barge is bumped by a tugboat.

Let q = the probability that an intervening injurer appears (e.g., the barge is bumped by a tug). We will assume that q is a random variable, like the other intervention probability s, and that it is independent of s. The probability of injury if the initial actor does not take care is therefore $E(q)r + (1-E(q))w$. Taking care (installing lifebuoys) is socially desirable if

$$x + E(q)[E(s)w + (1 - E(s))r]L + [1 - E(q)]wL < E(q)rL + (1 - E(q))wL$$

which is equivalent to

$$x < E(q)E(s)(r - w)L \quad . \tag{3}$$

Constrained by lack of information and by evidence rules, the court uses its observations of the intervention probabilities s_0 and q_0 to determine negligence. It follows that the injurer will be found negligent under the *ex post* evaluation of negligence if

$$\frac{x}{(r-w)L} < s_0 q_0 \quad . \tag{4}$$

Thus, if $z = sq$, and $H(z)$ is the cumulative distribution function, the barge owner will take care under negligence when

$$x < [1 - H\left(\frac{x}{(r-w)L}\right)]rL \ , \tag{5}$$

which is equivalent to the one-sided causation scenario except for the form of the distribution function.

b. Safe Lock Scenario

Another two-sided causation scenario similar to the one just studied involves the locking of a safe or some durable precaution designed to prevent an injury. The obvious example is where a hotel purchases a safe for the storage of valuables. The safe is effective, however, only if the hotel employees remember to lock it. In addition, nothing will happen unless thieves attempt to steal valuables from the hotel.

An alternative version of the same scenario: a railroad is transporting a dangerous chemical through a populated area. For example, in *Watson v. Kentucky & Indiana Bridge & R.R.*[18] a tank car containing gasoline derailed as a result of the defendant railroad's negligence, causing gasoline to spill. The intervening actor threw a lighted match onto the gasoline, causing an explosion that injured the plaintiff. The question was whether the intervening act was foreseeable. Obviously, there are many variations one could offer based on this example.

As a general matter, the railroad must decide whether to purchase a special lock for the release valve on the tank car holding the dangerous chemical. If it purchases the lock, someone must remember to actually lock the valve. In general, however, the risk of spillage is low unless an intervening actor deliberately opens the valve to release the chemical.

In this class of scenarios the effectiveness of taking care, by purchasing a lockable barrier, depends on whether the actor takes the intervening step of engaging the lock. On the other hand, the risk of an injury is minimal unless the intervening actor attempts to breach the barrier.

Let s = the probability that the actor engages the lock, and q = the probability that the intervening actor attempts to breach the barrier. I assume, as in the previous part, that the probability of attempting to breach the barrier is not dependent on the likelihood of a barrier existing.

Taking care is socially desirable in the Safe Lock Scenario if

$$x + E(s)wL + (1 - E(s))[E(q)r + (1 - E(q))w]L < E(q)rL + (1 - E(q))wL$$

which simplifies to $x < E(q)E(s)(r - w)L$. Since this is the same as (3), the actual determination of the care level is governed by (5).

c. Optimality of Care and Distortion Measure, Independent Interventions

[18] 126 S.W. 146 (Ky. 1910).

The foregoing examples suggest that, as a general matter, the care determination in independent interventions scenarios can be described by (5). This, in turn, implies the following:

Proposition 1: In the two-sided intervening causation scenario with independent interventions, the negligence test leads to socially excessive care if $(r - w)E(s)E(q) < r[1 - H(E(s)E(q))]$. *Care is socially optimal if equality holds and socially inadequate if the inequality is reversed.*

The incentive distortion measure for the independent interventions scenario is

$$D = \varphi - \frac{(1 - H(E(s)E(q))}{E(s)E(q)} \quad . \tag{6}$$

$D < 0$ implies that the negligence test induces socially excessive care. $D = 0$ is associated with optimal care, and $D > 0$ is associated with inadequate care.

3. Simulation 3: Two-Sided Causation, Beta Distribution Case

Now we simulate incentives for care for the independent interventions, two-sided causation scenarios examined previously (Boat Safety, Safe Lock).

The interesting question is whether the distortion from socially optimal care is greater in the two-sided causation scenario than in the one-sided scenario. Since the answer to this question depends on assumptions with respect to the productivity of care (φ) and the distributions of the intervention probabilities, we use simulations to examine the distortion from optimal care.

Following the same approach as in Figure 2, we allowed for the signals q and s to have Beta distributions where s is distributed $Beta_s(\alpha, \beta)$ and q is distributed $Beta_q(\gamma, \delta)$. The x axis in Figure 2 measures the product of the two mean signal values. The parameters for each of the distributions sum to 20 (i.e., $\alpha + \beta = 20$, $\gamma + \delta = 20$).

In carrying out the simulation, we fixed the degree of skewness on the s distribution and allowed the other to move from left skew to right skew. This allows us to replicate the simulation approach taken with the one-signal case examined earlier in Figure 2.

Specifically, the dark line fixes the distribution of s at the symmetric position and permits the distribution of q to run from a strong left skew to a strong right skew. As the skew moves from left to right, the value on the horizontal axis, $(\alpha/(\alpha + \beta))\times(\gamma/(\gamma + \delta))$, moves from left to right. We repeated the same exercise with different assumptions on α and β shown below.

As Figure 3 shows, the distortion levels in the two-sided causation scenario are greater than in the one-sided causation scenario simulated in Figure 2. Moreover, in order to find a set of parameter values which generated socially optimal care taking, we had to set the productivity of care at the highest level (φ = (.95 – .05)/.95 ≈ .95). For care productivity levels φ = .66 and φ = .89, care is socially excessive for all of the Beta parameter combinations tested.

The dotted curve in Figure 3 is the only one that crosses the zero distortion line and that crossing occurs where the value on the horizontal axis is 0.87. The dotted curve represents the most extreme right skew combination that we could implement in this simulation. For the dotted curve, s is distributed $Beta_s(19,1)$ and q is permitted to move from a strong left skew ($Beta_q(1, 19)$) to a strong right skew (($Beta_q(19,1)$)). Yet, even in this case, negative distortion values – signaling socially excessive care – are observed for all but two of the parameter combinations used for the q distribution. These results suggest that the optimal care outcome is unlikely to be observed in the two-sided causation scenario.

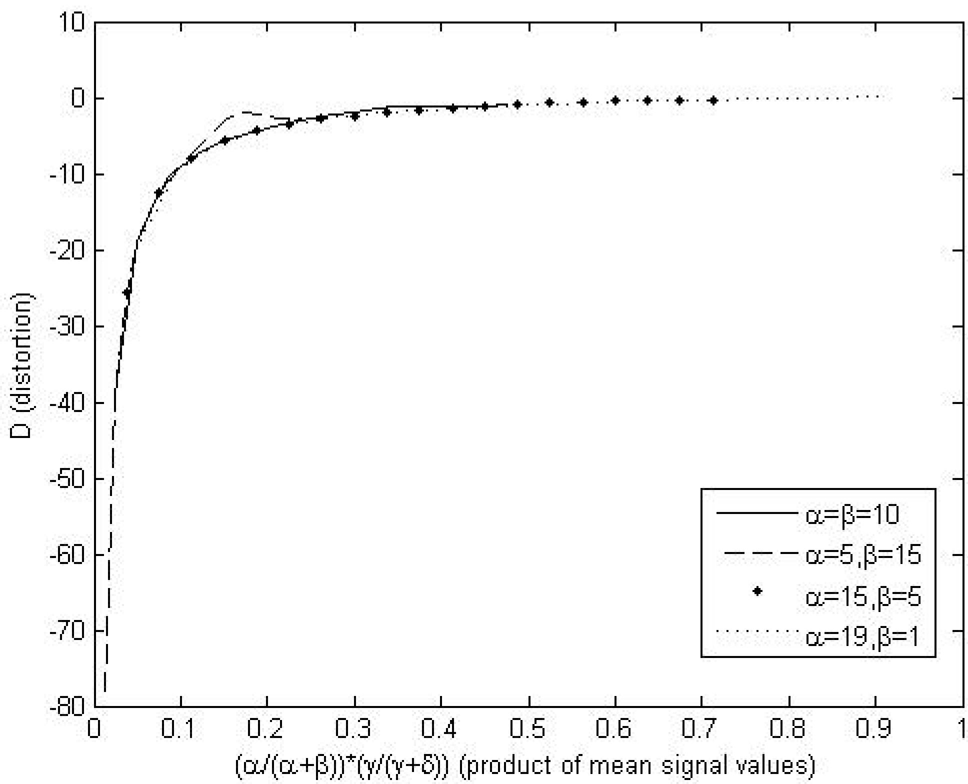

Figure 3: Distortion from Optimal Care, Two-Sided Causation, Beta Distribution Case (assuming φ ≈ .95)

C. Interdependent Interventions

We extend the analysis here to two-sided causation scenarios where intervention on the risk side depends on intervention on the care side. Although we provide no simulations, the distortion from optimality observed in the independent interventions scenarios appears to be even greater in the interdependent interventions scenarios.

1. Safe Lock Scenario II

The probability that an intervening criminal actor strikes depends on whether the initial actor takes care. For example, the initial actor decides whether to leave his keys in the car, and the intervening actor decides whether to attempt to steal the car. If the intervening actor sees that the keys are inside the car, he is more likely to steal the car.

Care is socially desirable if

$$x + E(s)rL + (1-E(s))wL < E(q)rL + (1-E(q))wL \ . \tag{7}$$

In this condition, the left-hand side represents the social cost when the initial actor (car owner) chooses to take care. Society bears the cost of taking care plus the expected cost of a car theft, given the car owner's decision to take care. The expected probability that the thief will intervene when the car owner takes care is $E(s)$. The right-hand side shows the cost to society when the car owner does not take care, in which case the expected intervention probability is $E(q)$. Condition (7) is equivalent to

$$x < [E(q) - E(s)](r - w)L \ . \tag{8}$$

A limited-information court will hold the actor liable under the negligence test if

$$x < (q_0 - s_0)(r - w)L \ . \tag{9}$$

This case is interesting because it indicates that taking care is never socially desirable in this scenario when $E(s) \geq E(q)$. It follows that if the intervention probabilities, q and s, are both from a symmetric distribution, taking care is never socially desirable. These implications are economically reasonable because if the expected intervention probability is higher when the car owner takes care, then taking care is a waste of resources.

The interesting feature of this intervening causation scenario is that the car owner may have an incentive to take care, given the structure of the negligence test, even when taking care could not possibly be socially desirable (for example, when $E(s) = E(q)$). The incentive distortion created by the negligence test is at least as severe in this scenario as in the preceding causation scenarios examined.

Substituting $v = 1 - s$ allows us to express (9) as the sum of two random variables, $v + q$. Using this approach, taking care is socially desirable if

$$x < [E(q) + E(v) - 1](r - w)L$$

Letting $H(z)$ represent the distribution function for the sum of random variables $z = q + v$, we have the following result.

Proposition 2: In the interdependent interventions scenario, the negligence test leads to socially excessive care if $(r - w)(E(q) + E(v) - 1) < r[1 - H(E(q)+E(v))]$. *Care is socially optimal if equality holds and socially inadequate if the inequality is reversed.*

The case of symmetric distributions is easiest to examine. For the symmetric case, $E(q) = E(v) = ½$, and $H(E(q) + E(v)) = H(1)$. Since $H(1)$ is the value of the distribution function evaluated at its median, and the distribution of the sum of two independent symmetric random variables is also symmetric, the median is the same as the mean, which implies $H(1) = ½$. Given this, the condition in Proposition 2 reduces to $0 < r/2$, where 0 is the marginal social value of care in this case. Thus, in the symmetric distribution case, some actors will have incentives to take care even under conditions in which care is never socially desirable, no matter how productive it appears to be based on the differential r-w.

2. Non-Exogenous Intervention

There are still more variations on the two-sided causation scenarios examined here. If the second actor (e.g., the thief) bases his decision, at least in part, on the initial actor's (the owner's) probability of intervention, then the probability of the second actor's intervention may be a function of the probability of the first actor's intervention. Consider for example, the Safe Lock Scenario where the second actor's probability of attempting to break the barrier (e.g., open the valve or open the safe door) is a function of the first actor's probability of intervention (locking the valve or safe door). If the second actor's intervention probability is simply a function of the first actor's intervention probability, then the scenario is no longer one of two-sided causation.

The models examined previously assume that the intervention probabilities are exogenous. Of course there are settings, in addition to the case where the second actor's intervention probability is dependent on the first actor's, where the exogeneity assumption would be inappropriate. Suppose, for example, that the first actor can choose or constrain his probability of intervention. The precaution decision involves investment in a durable precautionary measure and in constraining the first actor's probability of intervention. To take a specific example, suppose the first actor is the owner of a railroad tank car used to transport dangerous chemicals and the second actor is a vandal. The owner decides how much to invest in a lockable valve for the tank car, and how much to invest in monitoring employees to induce them to consistently lock the valve, all while knowing how the second actor's probability of intervention changes in response.

D. Solutions to the Excessive Care Problem

One reform that would greatly reduce the tendency to excessive care revealed in these models is for courts to follow the recommendation of Shavell (1985) by awarding a proportionate damages measure $\varphi L = (r - w)L/r$. Under proportionate damages, the distortion measure for the one-sided causation scenario becomes $D = 1 - (1\text{-}G(E(s))/E(s)$, which is equal to zero for any symmetrically distributed intervention probability. Thus, whatever the value of the productivity of care measure φ (between the limits of zero and one), the zero distortion (optimal care) outcome would be attainable. Similarly, for the two-sided (independent interventions) scenario, the distortion measure would be $D = 1 - (1\text{-}G(E(s)E(q))/E(s)E(q)$, with the same implication.

III. Conclusion

The early literature on causation demonstrates that if courts have full information, incentives for care are optimal if the likelihood of judicial error is zero (Grady, Kahan, Marks). The more realistic assumption, in our view, is that courts do not have full information. In particular, courts do not have information on the range and the probabilities of all of the intervening causal factors. We have allowed for the court to be in a position of Knightian uncertainty, in the sense that it does not know the distributions of the relevant intervention probabilities. The innovation of this paper is its consideration of intervening causal factors affecting both the impact of care and the impact of a failure to take care on the likelihood of injury (two-sided causation).

Under the more realistic informational assumptions here, incentives for care are not necessarily optimal in the rich set of causation scenarios typically confronted by courts. Our examination of one-sided and two-sided causation scenarios finds that care incentives are often distorted from optimality, and that the two-sided causation scenarios compound distortions (generally in the direction of excessive care) to a degree that suggests that the optimal care outcome is implausible. A proportionate damages measure, as originally suggested in Shavell (1985), provides a potential solution to this problem.

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Appendix

Definition 1: The random variable *X* is said to have a Beta type I distribution with parameters (a,b), $a>0, b>0$ denoted as $X \sim B^I(a,b)$, if its p.d.f. is given by

$$\{B(a,b)\}^{-1} x^{a-1}(1-x)^{b-1},\ 0<x<1,$$

where, $B(a,b)$ is the Beta function given by

$$B(a,b)=\Gamma(a)\Gamma(b)\{\Gamma(a+b)\}^{-1}$$

and the gamma function $\Gamma(n)=(n-1)!$.

Definition 2: The random variable *X* is said to have a hypergeometric function type I distribution, denoted by $X \sim H^I(\nu,\alpha,\beta,\gamma)$, if its p.d.f. is given by

$$\frac{\Gamma(\gamma+\nu-\alpha)\Gamma(\gamma+\nu-\beta)}{\Gamma(\gamma)\Gamma(\nu)\Gamma(\gamma+\nu-\alpha-\beta)} x^{\nu-1}(1-x)^{\gamma-1}\,{}_2F_1(\alpha,\beta;\gamma;1-x),\ 0<x<1,$$

where, ${}_2F_1(a,b;c;z)=1+\frac{ab}{1!c}z+\frac{a(a+1)b(b+1)}{2!c(c+1)}z^2+\cdots=\sum_{n=0}^{\infty}\frac{(a)_n(b)_n}{(c)_n}\frac{z^n}{n!}$,

$\gamma+\nu-\alpha-\beta>0$ and $\nu>0$.

Definition 3: Let X_1 and X_2 be independent, $X_i \sim B^I(a_i,b_i)$, $i=1,2$. Then, $X_1X_2 \sim H^I(a_1,b_2,a_1+b_1-a_2,b_1+b_2)$.

See Zarrozola and Nagar (2009).

1. Single Signal Case (Beta Distribution)

$$E(s)=\frac{a}{a+b}$$

$$G(E(s))=\int_0^{E(s)}\frac{1}{B(a,b)}x^{a-1}(1-x)^{b-1}\,dx$$

To compute the value, we used “betacdf” in Matlab.

$$D=\left(\frac{r-w}{r}\right)-\frac{(1-G(E(s)))}{E(s)}$$

where r, w are given.

2. Two Signal Case (Beta Distribution)

$$E(s) = \frac{a}{a+b},\ E(q) = \frac{c}{c+d}$$

Based on the Definition 3 above, the product of independent Beta variables follows $X_1 X_2 \sim H^I(a, d, a+b-c, b+d)$.

$$H(E(s)E(q)) = \int_0^{E(s)E(q)} \frac{\Gamma(b+a)\Gamma(d+c)}{\Gamma(b+d)\Gamma(a)\Gamma(c)} x^{\nu-1}(1-x)^{\gamma-1} {}_2F_1(d, a+b-c; a; 1-x)\,dx$$

To compute the values for the simulation, we used "int" in Matlab and assuming n=3 in ${}_2F_1(a,b;c;1-x)$.