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## Behavior under vague standards: Evidence from the laboratory

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# JENA ECONOMIC RESEARCH PAPERS



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## **Behavior Under Vague Standards: Evidence from the Laboratory**

by

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## Behavior Under Vague Standards: Evidence from the Laboratory

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**Abstract:** Doctrinal lawyers strive to reduce legal uncertainty based on the premise that difficult to predict legal consequences discourage socially desirable activities. Contributions from the economic theory of law suggest that increasing legal uncertainty can be socially beneficial. We test in an innovative laboratory experiment whether increasing the variability of an exogenous choice threshold (legal standard) increases or reduces socially desirable behavior. The results indicate a U-shaped relationship between increases in variability and activity choices: increases in variability first induce lower than optimal choices under an efficient standard (overcompliance), but eventually lead to greater than optimal choices under an efficient standard (undercompliance). We also find that overcompliance arises only under low degrees of standard variability. Moreover, increasing variability gradually crowds-out compliant choices. Finally, in the experiment minimal variability of the legal standard induces erratic individual behavior beyond socially satisfactory levels such that the standard loses its coordination function.

**Keywords:** legal uncertainty; vague legal standard; overcompliance and undercompliance; experimental law and economics; compliance crowding-out

**JEL classification:** C91, D02, K10

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## **1. Introduction**

In settings of legal uncertainty, a person faces difficulties to perfectly predict how a judge or public administration official will apply the law (e.g.: Popelier, 2000; Raitio, 2008). Which legal consequence will realize remains unclear in the sense that possible consequences are associated with some residual probability of occurring. For example, when an informed prediction yields a 90% chance of either winning or losing at trial, how the law will be applied is quite foreseeable. In this case, legal uncertainty is low. By contrast, given a 50%-level of predictability of either outcome, the legal consequence resulting from trial is not at all foreseeable. In this case, legal uncertainty is highest (D'Amato, 1983).

Theoretical conflict exists between doctrinal legal scholars and economists regarding the effects of legal uncertainty on rule-subjected individuals. On the one hand, an argument in doctrinal legal scholarship holds that difficult-to-predict legal consequences can crowd-out socially beneficial activities. This argument relates back to Max Weber's theory on legalism (Trubek, 1972; Weber, 1978). Consequently, doctrinal legal scholars on both sides of the Atlantic advocate reducing legal uncertainty (see e.g.: D'Amato, 1983; Popelier, 2000; Maxeiner, 2006, 2007; Raitio, 2008; Smits, 2012). On the other hand, results from economic theory reveal that increasing legal uncertainty can encourage socially beneficial activities. For instance, increases in the vagueness of a legal standard may reduce excessively compliant behavior that is inefficient (Craswell and Calfee, 1986). As another example, legal uncertainty can act as selective deterrent that discourages controversial actions while stimulating socially beneficial activities (Lang, 2014). Compared to their lawyer colleagues, economists emphasize optimal rule design and suggest that reducing legal uncertainty at all costs is not desirable.

In this article, we provide insight into the discussion about the effects of legal uncertainty on activity choices in three steps. First, we elaborate on the concept of legal uncertainty that we employ throughout our study. We do so by revisiting Craswell and Calfee (1986)'s model that analyses a person's activity choice under a vague legal standard. The vague legal standard is stochastic in the sense that it is drawn from a known probability distribution. Accordingly, there is a chance of false positives and false negatives, i.e., a court may mistakenly exonerate a noncompliant person or erroneously sanction a compliant person (see also: Kaplow, 1994). Changes in the dispersion of the probability distribution reflect different degrees of standard vagueness. As a result, Craswell and Calfee (1986) identify a U-shaped relationship between standard vagueness and activity choices such that increases in standard vagueness can reduce inefficient overcompliance. Second, we update the model's assumptions about a person's preference structure. We show that the doctrinal perspective on the discussion can be accommodated within the same model. Finally, to falsify either of the ensuing perspectives, we study individual behavior under vague legal standards in a controlled laboratory experiment.

In the experiment, 137 participants indicated an activity choices by positioning a slider. After their slider choice, we simulate a vague legal standard by drawing a choice threshold from a normal distribution known to the participants. If a participant's slider

choice was lower than the choice threshold, she was paid according to a payoff function reflecting her private benefit from the slider choice. If the slider choice was greater than the choice threshold, however, the participant had to return a specified amount of her private benefit and, thus, received a lower payoff than otherwise. To experimentally reflect different degrees of standard vagueness as measure of legal uncertainty, the experiment varied between subjects the standard deviation of the distribution determining the choice threshold. The experiment comprised six treatment groups with increasing degrees of standard vagueness.<sup>1</sup>

Our main results support the standard economic model of Craswell and Calfee (1986): a sufficiently low level of standard vagueness on average induces overcompliance; after a tipping point, however, a further increase of standard vagueness reduces and, eventually, eliminates overcompliant choices. Inefficiently overcompliant choices only obtain under low standard vagueness. Otherwise, activity choices under substantial standard vagueness are statistically indistinguishable from those under near absence of standard vagueness. Moreover, our data reveals important auxiliary results. First, the share of compliant (as opposed to non-compliant) choices gradually reduces with increasing standard vagueness. Second, as soon as standard vagueness exceeds the quasi-certain level, the share of socially desirable (as opposed to socially undesirable) choices sharply drops—to the extent that socially undesirable choices far outweigh socially desirable choices.

With this paper, we primarily contribute to previous research on negligence liability (e.g.: Shavell, 1980; Landes and Posner, 1981; Kahan, 1989), in general, and on the effect of vague legal standards (e.g.: Craswell and Calfee, 1986; Lang, 2014), in particular. In this respect, we provide experimental evidence on how standard vagueness affects the activity choice.

In addition, our study relates to other research streams. First, our results speak to different contributions in the deterrence literature. The deterrence hypothesis involves that criminal actions decrease in the probability of punishment (seminal: Becker, 1968). Experimental tests of the deterrence hypothesis mostly uncover confirmatory evidence (e.g.: Abbink, Irlenbusch, and Renner, 2002; DeAngelo and Charness, 2012; Rizzolli and Stanca, 2012; Schildberg-Hörisch and Strassmair, 2012; Khadjavi, 2015). These studies, however, only use point values as exogenous detection probabilities. By contrast, we employ an endogenous and dynamic detection probability that depends on a person's choice. Thereby we allow potential offenders to self-select into a tolerable detection probability. In addition, our study is not driven to achieve maximum deterrence, but rather optimal deterrence. Moreover, regarding deterrence researchers have suggested that accuracy is a method of increasing deterrence because fewer legal errors increase the disincentives to commit harmful acts (e.g. Kaplow, 1994; Polinsky and Shavell, 1989). Our results, however, indicate a non-monotonic relationship between accuracy and activity choice. Second, our results provide novel experimental evidence for the rules versus standards debate. A common argument is that *ex ante* uncertainty endemic in standards

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<sup>1</sup> Although the notion is contested that data from field experiments is more realistic (e.g.: Falk and Heckman, 2009), we acknowledge that the advantages of controlled laboratory experiments may come at the price of reduced external validity.

can lead to undesirable behavior. Specifically, risk-averse persons may forego socially desirable actions when exposed to an uncertain standard (e.g.: Kaplow, 1992; Korobkin, 2000). Our results indicate that the amount of foregone actions depends on the degree of standard vagueness. In fact, even after controlling for risk attitudes our participants do not significantly forego desirable actions in any treatment. Thus our results invalidate the argument against using standards in lieu of rules.

Section 2 derives predictions based on a formal model. Section 3 discusses the experimental design. Section 4 analyses the the data and reports the ensuing results. Section 5 discusses our findings before Section 6 concludes.

## 2. Theory & predictions

We derive predictions from a formal model that builds upon previous work of Craswell and Calfee (1986). We start by setting up the model and reviewing Craswell and Calfee (1986)'s results. We then add behavioral modifications to the original model.

Suppose a rational, fundamentally self-interested person can engage in an activity  $x$  with  $x \in [0, \bar{x}]$ , where  $\bar{x}$  is some upper natural or technological boundary. Exercising activity  $x$  is profitable for the person. Let  $b(x)$  represent these benefits and assume  $b(x)$  to be twice differentiable and concave, i.e.,  $b'(x) > 0$ ,  $b''(x) \leq 0$ . Moreover, engaging in activity  $x$  imposes costs on others. Let  $e(x)$  denote this negative externality and assume  $e(x)$  to be twice differentiable and convex, i.e.,  $e'(x) > 0$ ,  $e''(x) \geq 0$ .

Further suppose a lawmaker or judge wants to regulate activity  $x$  by setting a legal standard  $x_L$  with  $x_L < \bar{x}$ . The legal standard  $x_L$  is a maximum standard: when a person chooses  $0 \leq x \leq x_L$  she is compliant; when she chooses  $x_L < x \leq \bar{x}$  she violates the legal standard. For instance, think of  $x_L$  as a speed limit, maximum working hours per week, or a cap on noise pollution. Moreover, assume that courts will hold a person violating  $x_L$  fully liable for the costs that her choice of  $x$  imposes on others. When non-compliant, she has to pay damages  $d(x)$  that perfectly compensate for the negative externality, i.e.,  $d(x) = e(x)$ .<sup>2</sup>

Assume that the legal standard is set at the amount of activity  $x$  that maximizes social welfare, i.e.,  $x_L = x_S$ . Formally,  $x_S$  solves the problem  $\max_x [b(x) - e(x)]$  and thus satisfies the condition  $b'(x) = e'(x)$ . Following Craswell and Calfee (1986), we can thus define over- and undercompliance relative to the socially optimal amount of activity  $x$ . When a person chooses  $x < x_S$ , from a societal perspective she practices too little of activity  $x$ . She is overcompliant. Conversely, when a person chooses  $x > x_S$ , she carries out too much of activity  $x$ . She is undercompliant. Both overcompliance and undercompliance are socially undesirable because any choice  $x \neq x_S$  leads to a welfare loss.

At least since Brown (1973), negligence models mostly assume legal certainty in that they rely on a precise, deterministic legal standard (e.g.: Shavell, 1980; Landes and Posner, 1981; Grady, 1983; Kahan, 1989). By contrast, we model a stochastic legal standard to

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<sup>2</sup> Because  $d(x) = e(x)$ , for the remainder of the paper we will not further differentiate between damages and external costs and use  $e(x)$  for convenience.

represent standard vagueness as one variety of legal uncertainty. A person who chooses  $x$  only knows that with increasing  $x$  there is a probability  $P(x_L < x) = F(x)$ , with  $F'(x) > 0$ , that a court will hold her in violation of the legal standard. Conversely, with probability  $P(x_L \geq x) = 1 - F(x)$  a court will find a person in compliance with the legal standard. Intuitively, the stochastic nature of  $x_L$  may result, for instance, from the varying and possibly erroneous interpretation of the standard by various judges and administrative officials. Formally, assume that  $F(x)$  is a cumulative distribution function with

$$F(x) \equiv \int_0^x f(t) dt,$$

where  $f(x) \equiv F'(x)$  is the associated probability density function. As functional form, we assume that  $x_L$  is normally distributed around the socially optimal level  $x_S$ , i.e.,  $x_L \sim \mathcal{N}(x_S, \sigma)$ ,<sup>3</sup>. Thus we denote the ensuing probability as  $\Phi(x)$  and its first derivative as  $\phi(x)$ .

This modelling step corresponds with the way in which legal scholars have conceptualized legal uncertainty. Legally relevant decisions concern an informed prediction of how the courts will apply the law when presented with some dispute (cf.: Holmes, 1897; Popelier, 2000; Raitio, 2008). Legal uncertainty thus creates a prediction problem and legal uncertainty can be understood as a

“situation that obtains when the rule that is relevant to a given act or transaction is said [...] to have an expected [...] outcome at or near the 0.5 level of predictability”  
(D’Amato, 1983, p. 2).<sup>4</sup>

In this sense, a legal rule affects a person’s behavior to the extent that the person perceives the uncertainty of being found in violation or in compliance with the rule. In the present model, a higher  $\sigma$  implies a larger interval around the legal standard  $x_L = x_S$  that yields a prediction close to the 0.5 level of being found either violating or complying with the legal standard. Put differently, the location of the legal standard becomes less predictable with increasing  $\sigma$ . Measures of dispersion of the underlying probability distribution of the legal standard then reflect the degree of standard vagueness and legal uncertainty.

As we assume that probability distributions are known, our approach to modelling “legal uncertainty” is incommensurate with how economists think about uncertainty. Economists understand uncertainty as risk that is immeasurable: an event is uncertain if it may or may not happen in the future and the probabilities of the event occurring or not are unknown (Knight, 1921). Technically, this model of legal uncertainty concerns

<sup>3</sup> As a robustness check, Figure 5 in Appendix A illustrates predictions when  $x_L$  is uniformly distributed. Changing the underlying distribution does not change the basic analytical results and hypotheses.

<sup>4</sup> This needs to be clearly differentiated from another, operationally different definition of legal uncertainty. Legal uncertainty can be understood as a situation that emerges when the legal system contains at least one legal problem whose correct solution is undeterminable, e.g., a case that cannot be decided in an identifiably and uniquely correct way. In this sense, Dworkin (1977, p. 286) speaks of “ties”.

risky decision-making because probabilities are known for each choice  $x$ . This approach is in line with the conceptualization of legal uncertainty in legal scholarship, however. Moreover, recent research in law and economics not only studies legal uncertainty as Knightian uncertainty (e.g.: Schildberg-Hörisch and Strassmair, 2012) but also utilizes known probability distributions (e.g.: Lang, 2014).

## 2.1. Standard preferences & risk-neutral persons

To specify a person's preference structure, we initially consider a risk-neutral person who derives utility from her choice of  $x$  according to the utility function

$$u_{RN}(x) = \begin{cases} b(x) & \text{for } x \leq x_L \text{ (compliance)} \\ b(x) - e(x) & \text{for } x > x_L \text{ (violation)} \end{cases}. \quad (1)$$

As outcome  $x > x_L$  occurs with probability  $\Phi(x)$ , for any choice of  $x$  her expected utility is

$$U_{RN}(x) = b(x) - \Phi(x) e(x). \quad (2)$$

Because we assume utility to be piecewise linear in wealth,  $U_{RN}(x)$  coincides with the expected value of net benefits. This formulation is equal to the original optimization problem of Craswell and Calfee (1986)'s risk-neutral agent. This congruence deserves emphasis because Craswell and Calfee (1986) did not make their agent's utility function explicit – with important consequences for the extension to risk-averse agents (see Appendix B).

To understand a risk-neutral person's incentives at the socially optimal level  $x_S$ , we differentiate  $U_{RN}(x)$  with respect to  $x$

$$\frac{\partial U_{RN}(x)}{\partial x} = b'(x) - \phi(x) e(x) - \Phi(x) e'(x) \quad (3)$$

and evaluate this result at the social optimum  $x_S$  where  $b'(x) = e'(x)$

$$\left. \frac{\partial U_{RN}(x)}{\partial x} \right|_{x_S} = (1 - \Phi(x_S)) b'(x_S) - \phi(x_S) e(x_S). \quad (4)$$

The first term of expression (4) describes the gains for the potential defendant from marginally increasing  $x$ . The marginal benefits are discounted by the probability  $1 - \Phi(x_S)$  that a person is found compliant. The second term of expression (4) represents the offsetting effect identified by Craswell and Calfee (1986). Marginal increases in  $x$  also increase the probability of being held liable. A utility maximizing person has an incentive to choose an individually optimal amount  $x^* < x_S$  (overcompliance) when



expression (4) is negative and an incentive to choose an individually optimal level  $x^* > x_S$  (undercompliance) when expression (4) is positive.

As a formal extension to Craswell and Calfee (1986), we derive from (3) the effect of standard vagueness on a person's optimal choice  $x_{RN}^*$  by

$$\frac{\partial U_{RN}(x_{RN}^*)}{\partial x_{RN}^*} \stackrel{!}{=} 0$$

and get  $x_{RN}^* = x_{RN}^*(\sigma)$ .<sup>5</sup> That is, the individually optimal choice  $x_{RN}^*$  is a function of the vagueness measure  $\sigma$ . The response function describes a risk-neutral person's optimal choice given a specific degree of standard vagueness. The dashed line in Figure 1 on page 8 illustrates the relation between  $x_{RN}^*$  and  $\sigma$ . The ordinate of the graph in Figure 1 represents the individually optimal choice  $x^*$  relative to the socially optimal level  $x_S$  and the legal standard  $x_L$ . The abscissa of the graph represents  $\sigma$  as a measure of vagueness of the legal standard. The response function  $x_{RN}^*(\sigma)$  resembles the characteristic pattern identified by Craswell and Calfee (1986): a sufficiently low level of  $\sigma$  initially induces overcompliance; an increase of standard vagueness beyond a tipping point, however, reduces overcompliance; eventually, overcompliance turns into undercompliant individually optimal choices. Two noteworthy results emerge. First, reducing standard vagueness does not necessarily improve the compliance decision. The difference between  $x^*$  and  $x_S$  describes how much individually optimal behavior deviates from socially optimal behavior. Despite a reduction in standard vagueness, this difference increases when standard vagueness is sufficiently high.<sup>6</sup> Second, a specific degree of standard vagueness  $\sigma^* > 0$  leads to socially optimal compliance decisions, i.e.,  $x_{RN}^*(\sigma^*) = x_{RN}^*(0) = x_S$ . When a precise standard is impossible to implement, the existence of  $\sigma^*$  implies that increasing (reducing) the degree of standard vagueness can be socially beneficial given initially overcompliant (undercompliant) behavior.

## 2.2. Standard preferences & risk-averse persons

We are interested in the behavioral consequences of legal uncertainty and extend the analysis by gradually incorporating or modifying assumptions about how a person decides. Our first behavioral modification concerns risk attitude. Instead of assuming that a person is risk-neutral, we assume that a person exhibits risk aversion. We continue to model society as risk-neutral regarding the social benefits and costs from activity  $x$ . Therefore, the socially optimal amount  $x_S$  remains unchanged.<sup>7</sup>

<sup>5</sup> A mathematical solution to derive  $x_{RN}^*(\sigma)$  is not possible because  $\Phi(x)$  has no closed form representation. Therefore, we simulate the response functions  $x_i^*(\sigma)$ ,  $i \in \{RN, RA, KR\}$ , in Figure 1 using the software environment R. For specification and parametrization of all underlying functions, see Appendix C.

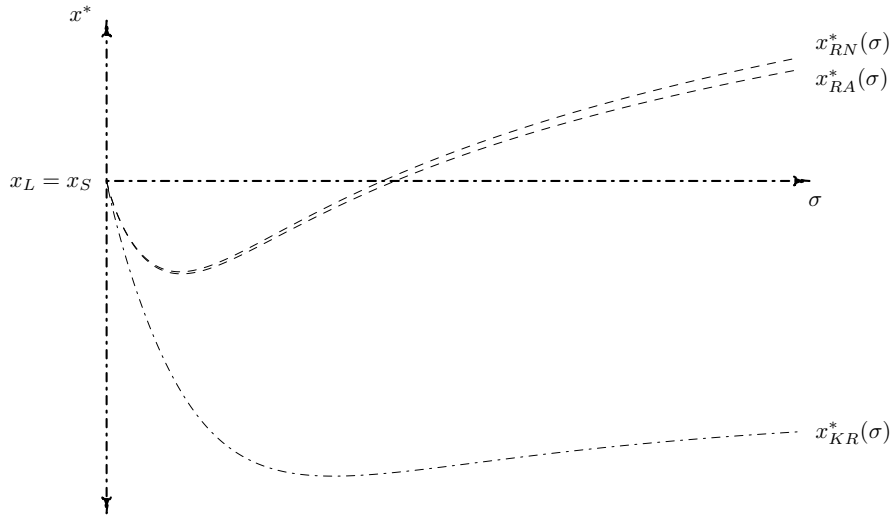
<sup>6</sup> Given a reduction in  $\sigma$ , the difference between  $x^*$  and  $x_S$  may especially increase when the legal standard is not distributed around the socially optimal level. See Craswell and Calfee (1986) for an extensive analysis within the risk-neutral framework. We do not test this case.

<sup>7</sup> We deviate here from Craswell and Calfee (1986) who assume that society is only risk-neutral regarding the social costs of a person's activity and that, therefore,  $x_S$  is determined by solving

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**Figure 1:** Over- and undercompliance for different preference structures

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Consider a rational, fundamentally self-interested person that is averse to risk. She has a twice differentiable utility function  $u(\cdot)$  with  $u'(\cdot) > 0$ ,  $u''(\cdot) < 0$  (concavity). As her utility over absolute income depends on her choice of  $x$ , she derives utility from

$$u_{RA}(x) = \begin{cases} u(b(x)) & \text{for } x \leq x_L \text{ (compliance)} \\ u(b(x) - e(x)) & \text{for } x > x_L \text{ (violation)} \end{cases}. \quad (5)$$

Differentiating her expected utility with respect to  $x$  and evaluating this result at the social optimum  $x_S$  where  $b'(x) = e'(x)$  yields

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$\max_x [u(b(x)) - e(x)]$ . This assumption strikes us as inconsistent. If one evaluates  $b(x)$  through the utility function of the person choosing  $x$ , one should consistently evaluate  $e(x)$  through the utility function of the person suffering the external cost. Moreover, risk preferences in society are heterogeneous. A regulator will hardly be able to specify an aggregate risk preference that sufficiently takes into account all idiosyncrasies of members of said society. Instead, we adopt the idea of a rationality default (Schwartz, 2015): when the facts are unobtainable or ambiguous, regulators should refrain from behavioral assumptions. This approach is “autonomy preserving, administrable, and coherent” (Schwartz, 2015, p. 1). The coherent application of the risk-neutral standard  $x_S$  is also experimentally motivated: in the experiment we only define one activity benchmark for all participants instead of a specific activity benchmark for each participant given her *ex ante* elicited utility function.

$$\frac{\partial U_{RA}(x)}{\partial x} \Big|_{x_S} = (1 - \Phi(x_S)) u'(b(x_S)) b'(x_S) - \phi(x_S)[u(b(x_S)) - u(b(x_S) - e(x_S))]. \quad (6)$$

Expression (6) is similar to the risk-neutral case in expression (4). The first term describes the gains for a risk-averse person of marginally increasing  $x$  if found compliant ( $x \leq x_L$ ). The second term represents the offsetting effect that marginal increases in  $x$  also increase the probability of being held liable ( $x > x_L$ ). This marginal increase is weighted by the opportunity cost of being found violating the legal standard. Similar to expression (4), a person has an incentive to choose  $x^* < x_S$  when expression (6) is negative. Conversely, she has an incentive to choose  $x^* > x_S$  when expression (6) is positive.

Analogous to the risk-neutral case, we obtain a risk-averse person's optimal choice  $x_{RA}^*$  by simulating the response function  $x_{RA}^*(\sigma)$ . The solid line in Figure 1 depicts this response function.  $x_{RA}^*(\sigma)$  shows a pattern very similar to  $x_{RN}^*(\sigma)$ : standard vagueness initially induces overcompliance but, as vagueness increases just enough, overcompliance will turn into undercompliance. Moreover, Figure 1 reveals that  $x_{RA}^*(\sigma) < x_{RN}^*(\sigma)$  over the entire range of  $\sigma$ . This result suggests that the domain of overcompliance is larger and that overcompliance is more severe compared to the risk-neutral case. By contrast, the domain of undercompliance is smaller and undercompliance is less severe. Craswell and Calfee (1986, p. 301) also find that risk aversion increases the likelihood of overcompliance. Compared to their result, however, the effect of risk aversion in the present model is much less pronounced. This difference is driven by an implicit assumption of Craswell and Calfee (1986, p. 301). In addition to risk aversion, they assume asset isolation. Under this assumption a person separates different payoff streams and computes utility for each of the payoffs separately. By contrast, the present model assumes asset integration: a person first computes final wealth and then evaluates final wealth through her utility function. Appendix B elaborates on this difference.

### 2.3. Reference-dependent preferences

Our second modification changes the assumption on how individuals evaluate outcomes. We incorporate into the model another empirically established finding about human behavior: hedonic consequences of outcomes depend not only on absolute outcomes, but also on how these outcomes change relative to a reference point (cf.: Barberis, 2013). Reference-dependent preferences successfully explain observed behavior that is seemingly at odds with standard economic predictions. For instance, reference-dependent preferences are useful to understand why taxi drivers stop working when their earnings are unexpectedly high (Camerer, Babcock, Loewenstein, and Thaler, 1997; Crawford and Meng, 2011), why sellers overprice their property when facing nominal losses in a real-estate crisis (Genesove and Mayer, 2001), and why contestants increase effort in contests with a higher proportion of winners than losers than in contests designed to yield less winners than losers (Lim, 2010). In the legal context, reference-dependent preferences, e.g., help explain why defendants are more reluctant than plaintiffs to accept

settlement offers (Rachlinsky, 1996) and why plaintiff's prefer contingent contracts, whereas defendants prefer to pay their attorneys fixed hourly fees (Zamir and Ritov, 2010).

Specifically, we build upon Kőszegi and Rabin (2006, 2007)'s modelling framework. Let overall utility over some good  $y$  consist of an absolute, purely outcome-based utility component  $m(y)$  and a relative, reference-dependent gain-loss utility component  $\mu(y - r)$ . While the former term describes the intrinsic utility a person obtains from  $y$ , the latter term describes how a person feels about changes in utility obtained from  $y$  relative to  $r$ . Formally, overall utility is

$$u(y | r) \equiv m(y) + \eta \mu(y - r).$$

Parameter  $\eta \geq 0$  weighs the importance of gain-loss utility relative to outcome-based utility. Without loss of generality, we assume  $\eta = 1$  for the remainder of the paper. We further assume that a person's absolute utility  $m(\cdot)$  is unbounded, strictly increasing, and (weakly) concave, i.e.,  $m'(\cdot) \geq 0$  and  $m''(\cdot) \leq 0$ .

Gain-loss utility  $\mu(\cdot)$  satisfies the implicit or explicit assumptions about the value function in prospect theory (see: Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Kőszegi and Rabin, 2006). The gain-loss utility function  $\mu(y - r)$  is

$$\mu(y - r) \equiv \begin{cases} m(y - r) & \text{for } y \geq r \\ -\lambda m(-(y - r)) & \text{for } y < r \end{cases} \quad (7)$$

Parameter  $\lambda \geq 1$  describes how much the agent weighs losses relative to gains. When  $\lambda > 1$ ,  $\mu(\cdot)$  is steeper for losses than for gains, i.e., the person is loss averse. Moreover,  $m(\cdot) \equiv (\cdot)^\alpha$ , where parameter  $\alpha$  measures diminishing sensitivity of the gain-loss utility function. We assume  $0 < \alpha < 1$  such that  $\mu(\cdot)$  is concave in the gain domain and convex in the loss domain. This assumption is also consistent with the assumptions about the absolute utility component  $m(\cdot)$ .

To specify the context at hand, let a person derive utility from monetary income, i.e.,  $y = w(x)$ . Similar to expression (2), a person's monetary income  $w(x)$  results from a gamble  $(b(x), 1 - \Phi(x); b(x) - e(x), \Phi(x))$ . That is, final wealth is stochastic.

The definition of the reference point  $r$  is crucial to predict behavior. Starting with Kahneman and Tversky (1979), most models of reference-dependent preferences equate the reference point with the status quo. In this sense, reference points are mostly deterministic and fixed exogenously. Consistently following Kőszegi and Rabin (2006, 2007), we assume a non-deterministic reference point that is formed by a person's lagged expectations about relevant outcomes of her choice. Intuitively, when a person codes recent beliefs about outcomes as a reference point, she evaluates any realized outcome by comparing it to all possible outcomes. Each comparison is weighted by the *ex ante* probability that the alternative outcome occurs. In this sense, expectation-based reference points are stochastic. Moreover, let individuals form fully rational expectations: a person correctly predicts her choice set, how her choice influences the distribution of possible outcomes, and her hedonic response.

From her choice of  $x$  a person with expectation-based reference-dependent preferences derives utility

$$u_{KR}(x) = \begin{cases} m(b(x)) + \Phi(x) m(e(x)) & \text{for } x \leq x_L \text{ (compliance)} \\ m(b(x) - e(x)) - (1 - \Phi(x)) \lambda m(e(x)) & \text{for } x > x_L \text{ (violation)} \end{cases}. \quad (8)$$

Intuitively, if a court finds a person compliant ( $x \leq x_L$ ), the person experiences absolute utility  $m(b(x))$  from the private benefits of her choice  $x$ . Moreover, she experiences an additional utility  $\Phi(x) m(e(x))$  from the comparison of the actual outcome compared to the counterfactual violation of  $x_L$  (gain). Conversely, if a court holds a person liable ( $x > x_L$ ), she generates utility from her private benefits less the compensation payment  $m(b(x) - e(x))$ . Further, she experiences an additional disutility  $(1 - \Phi(x)) \lambda m(e(x))$  relative to the expectation of being found compliant with  $x_L$  (loss).

Differentiating her expected utility with respect to  $x$  and evaluating the result at the socially optimal level  $x_S$ , where  $b'(x) = e'(x)$ , yields

$$\begin{aligned} \left. \frac{\partial U_{KR}(x)}{\partial x} \right|_{x_S} &= (1 - \Phi(x_S)) m'(b(x_S)) b'(x_S) \\ &\quad - \phi(x_S) \left[ m(b(x_S)) - m(b(x_S) - e(x_S)) \right] \\ &\quad + \phi(x_S) (\lambda - 1) \Phi(x_S) m(e(x_S)) \\ &\quad - (1 - \Phi(x_S)) (\lambda - 1) \left[ \phi(x_S) m(e(x_S)) + \Phi(x_S) m'(e(x_S)) e'(x_S) \right]. \end{aligned} \quad (9)$$

The first and second term describe absolute effects from marginally increasing  $x$  similar to expression (6). For  $x \leq x_L$  the decision-maker obtains a marginal benefit that is discounted by the probability  $1 - \Phi(x_S)$  but he also bears the opportunity costs for  $x > x_L$  as  $\Phi(x_S)$  marginally increases. Due to reference dependence, we find two additional effects. As the third term describes, marginally increasing the likelihood of  $x > x_L$  (violation) also increases the potential gain experience if this outcome is not realized. The fourth term captures that marginally increasing  $x$ , however, also threatens an increased loss when violating  $x_L$ . This countervailing effect is discounted by  $1 - \Phi(x)$ . Again, a person has an incentive to choose  $x^* < x_S$  when expression (9) is negative. Conversely, she has an incentive to choose  $x^* > x_S$  when expression (9) is positive.

We obtain the optimal choice  $x_{KR}^*$  by simulating the response function  $x_{KR}^*(\sigma)$  analogous to the risk-neutral and the risk-averse case. The dot-dashed line in Figure 1 depicts the ensuing relationship. Under expectation-based reference-dependent preferences, an increase in standard vagueness  $\sigma$  leads to a rapid drop of the individually optimal choice (overcompliance). However,  $x_{KR}^*(\sigma)$  exhibits a much less pronounced tipping point. After the initial drop, the extent of overcompliant behavior does not decrease substantially with increasing standard vagueness. We infer from expressions (9) and (6) that the difference between  $x_{KR}^*(\sigma)$  and  $x_{RA}^*(\sigma)$  depends on the loss aversion parameter  $\lambda$  because both expressions are equal when  $\lambda = 1$ . Depending on the specific definition, the elicitation

method, and the estimation approach, estimates of the loss aversion coefficient take on values from 1.43 to 4.8 (cf.: Abdellaoui, Bleichrodt, and Paraschiv, 2007; Abdellaoui, Bleichrodt, and L'Haridon, 2008). Despite this volatility, the canonical value as reported by Tversky and Kahneman (1992) is  $\lambda = 2.25$  and researchers commonly embrace  $\lambda \approx 2$  as a rule of thumb (e.g.: Hossain and List, 2012). For all these specifications of  $\lambda$  our simulations indicate that  $x_{KR}^*(\sigma) < x_S$  over the entire range of  $\sigma$ . That is, any amount of standard vagueness induces overcompliance. Importantly, this analytical result resonates with the argument from legal scholarship that legal uncertainty undermines socially beneficial activities and inhibits economic development.

## 2.4. Summary & hypotheses

The theoretical conflict between doctrinal legal scholarship (e.g.: D'Amato, 1983; Maxeiner, 2007; Smits, 2012) and economic theory of law (e.g.: Calfee and Craswell, 1984; Craswell and Calfee, 1986; Lang, 2014) about the effects of legal uncertainty is by no means trivial academic finger wrestling. We modelled legal uncertainty as vague standard in a simple negligence model. The formal analysis supports both views depending on the set of assumptions about how persons decide. Given a person's preference structure, the model thus generates equivocal predictions about the behavioral consequences of vague standards. The equivocal predictions call for experimental testing.

We formulate our research hypotheses in line with the findings in law and economics. Calfee and Craswell (1984) and Craswell and Calfee (1986) propose that, as standard vagueness  $\sigma$  increases, a person's activity choice first decreases and then increases again. We obtain the same result from our expected utility model for risk neutral and risk averse agents (see Figure 1). Therefore, we hypothesize:

**Hypothesis 1:** As standard vagueness  $\sigma$  increases, activity choices first decrease and then increase again. That is, the relation between standard vagueness and activity choice designates a U-shape.

Moreover, the U-shape between standard vagueness and activity choice implies that overcompliant behavior is more likely to be observed under lower degrees of standard vagueness than under higher degrees of standard vagueness. Overcompliant behavior will thus more easily emerge at low levels of standard vagueness as opposed to high levels of standard vagueness. We thus hypothesize:

**Hypothesis 2:** Overcompliant behavior will emerge at low levels of standard vagueness and not at high levels of standard vagueness.

### 3. Experimental design

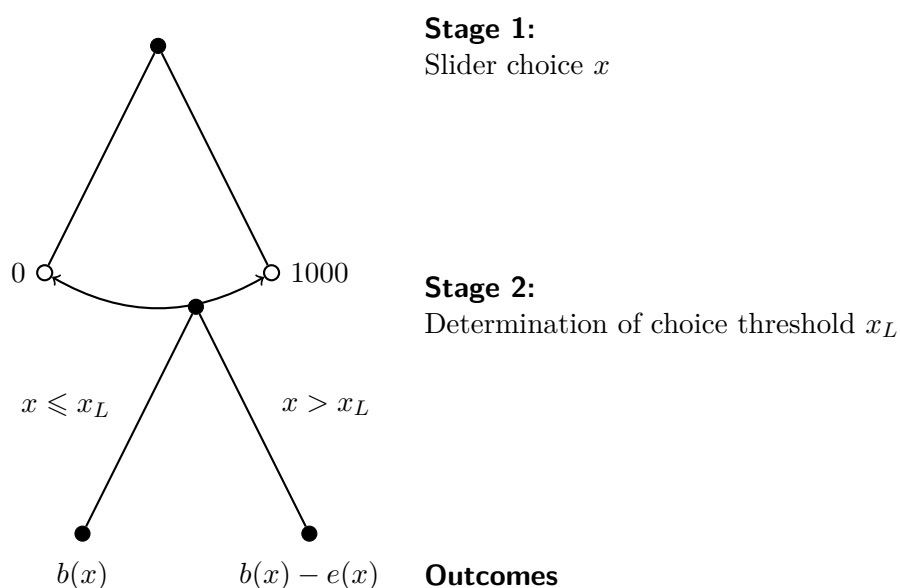
#### 3.1. Task & treatments

To emulate the theoretical problem in the laboratory, the main task of the experiment consisted of two stages. Figure 2 illustrates the main task. In the first stage, participants chose an “activity level” between 0 and 1000 units on a continuous slider (slider choice  $x$ ). We randomized the initial slider position because a fixed initial position potentially anchors, and thereby systematically distorts, participants’ slider choice.

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**Figure 2:** Game representation of the main task

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In the second stage, a random draw determined a choice threshold  $x_L$ . This random draw was defined by a normal distribution. Across all treatments, the mean of the normal distribution was set to 500.<sup>8</sup> To represent different degrees of standard vagueness, treatments only differed in the standard deviation  $\sigma$  of the normal distribution. Altogether, the experiment comprised  $i = 1, \dots, 6$  treatments with  $\sigma_i \in \{1, 100, 200, 300, 400, 500\}$ . Accordingly, the names of the treatments are SD001, SD100, SD200, SD300, SD400, and SD500. The experiment employed a between-subjects design: participants were randomly assigned to only one treatment.

After the draw of the choice threshold, the program compared a participant’s slider choice with the choice threshold to determine her payoff. If a participant chose a slider

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<sup>8</sup> Given our parametrization, a slider position of 500 corresponds to the social optimum  $x_S$  in the theoretical model. Therefore, setting the mean of the normal distribution to 500 reflects the idea that a regulator sets an efficient legal standard.

position less than or equal to the choice threshold (compliance:  $x \leq x_L$ ), she would gain the payoff  $b(x)$  in experimental currency units (ECU). If her slider choice was greater than the choice threshold (violation:  $x > x_L$ ), however, she only received the reduced payoff  $b(x) - e(x)$  in ECU. The parametrization of the task corresponds to Craswell and Calfee (1986)'s specifications used in their Table 1.<sup>9</sup> Specifically, participants' payoffs given the slider choice were

$$\Pi(x) = \begin{cases} b(x) = 50 \ln(x) & \text{for } x \leq x_L \text{ (compliance)} \\ b(x) - e(x) = 50 \ln(x) - 0.1x & \text{for } x > x_L \text{ (violation)} \end{cases}.$$

Participants' slider choices were incentivized and translated from ECU to EUR with a conversion rate of 0.03. Altogether, the main task consisted of six repetitions of these two stages to capture potential learning effects.

A graphical interface providing information for the slider choice accompanied the choice task. First, over the entire range of the slider, participants received a graphical representation of the probability that their slider choice would exceed the choice threshold. This representation corresponded to the cumulative density function underlying the random draw of the choice threshold. Second, the interface showed a graphical representation of the slider-choice-dependent payoff, both for the event that a participant's slider choice was smaller than or equal to the choice threshold and for the event that the slider choice exceeded the choice threshold. Third, the interface also provided information about the potential consequences of the current slider position to further increase salience of the payoffs, the probabilities of each event occurring, and their dependence on the slider position. We conveniently clarified the payoffs and probabilities for each event right next to the corresponding graphical payoff representation. Thus, for any slider position, participants could see the specific payoffs and the associated probabilities. As people frequently struggle with numerical probability descriptions (cf.: Cokely, Galesic, Schulz, Ghazal, and Garcia-Retamero, 2012; Peters, 2012), the interface also depicted the specific probabilities in a pie chart varying with the slider position. We kept the choice interface predominantly graphical. The experiment aimed at creating the least abstract choice environment while preserving as much control as possible. Figure 7 in Appendix D depicts a sample decision screen from the experiment.

After the main task, we conducted two incentivized post-tests relevant to the theoretical predictions. The first post-test elicited risk preferences following a multiple price list (MPL) approach (Holt and Laury, 2002; Gneezy, Imas, and List, 2015). The second post-test elicited participants' preferences over gains and losses (Abdellaoui, Bleichrodt, and L'Haridon, 2008).

### **3.2. Procedure & sample**

The experiment was conducted in January 2015 in the experimental laboratory of Friedrich Schiller University Jena. Altogether, 137 student subjects participated in the

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<sup>9</sup> The same mathematical specifications determine the response functions in Figure 1.



experiment.<sup>10</sup> Table 1 contains further information about the sample. Upon arrival at the lab, participants were randomly allocated to their cubicle and their treatment group by drawing a number from an urn. The experiment comprised eight sessions with three treatment groups each, i.e., SD001, SD100, SD200 in sessions 1-4 and SD300, SD400, SD500 sessions 5-8.

**Table 1:** Sample statistics per treatment and overall

	SD001	SD100	SD200	SD300	SD400	SD500	overall
# participants	24	24	21	24	24	20	137
% participants	17.52	17.52	15.33	17.52	17.52	14.60	100.00
% female	58.33	50.00	66.67	58.33	45.83	50.00	54.74
# Age (avg.)	25.44	26.24	25.24	25.78	25.18	26.67	25.74
field of study: law	0	3	5	0	1	3	12
economics	4	4	4	5	3	4	24
natural science	3	6	3	6	5	5	28
other	17	11	9	13	15	8	73

Because the choice in the main task was complex and participants confronted probability distributions, they received video instructions instead of mere textual instructions. The 11 minute video provided detailed information about the functionality of and the information displayed on the graphical interface, about the payoff structure, about the choice threshold, and about the probability distributions underlying its determination.<sup>11</sup> The instructions and the choice interface contained neutral language to avoid contextual associations and label effects. To ensure that participants understood the video instructions, they had to correctly answer a set of control questions. Without a correct answer, they could not advance to the main task. After the main task, participants completed the two post-tests. All sessions lasted approximately 45 minutes.

At the end of each session, one of the eight rounds—six rounds in the main task and two post tests—was randomly selected for payment. Altogether, participants received a payment between 6.30 EUR and 15.10 EUR including a show-up fee. Participants earned 8.70 EUR on average.

## 4. Analysis & Results

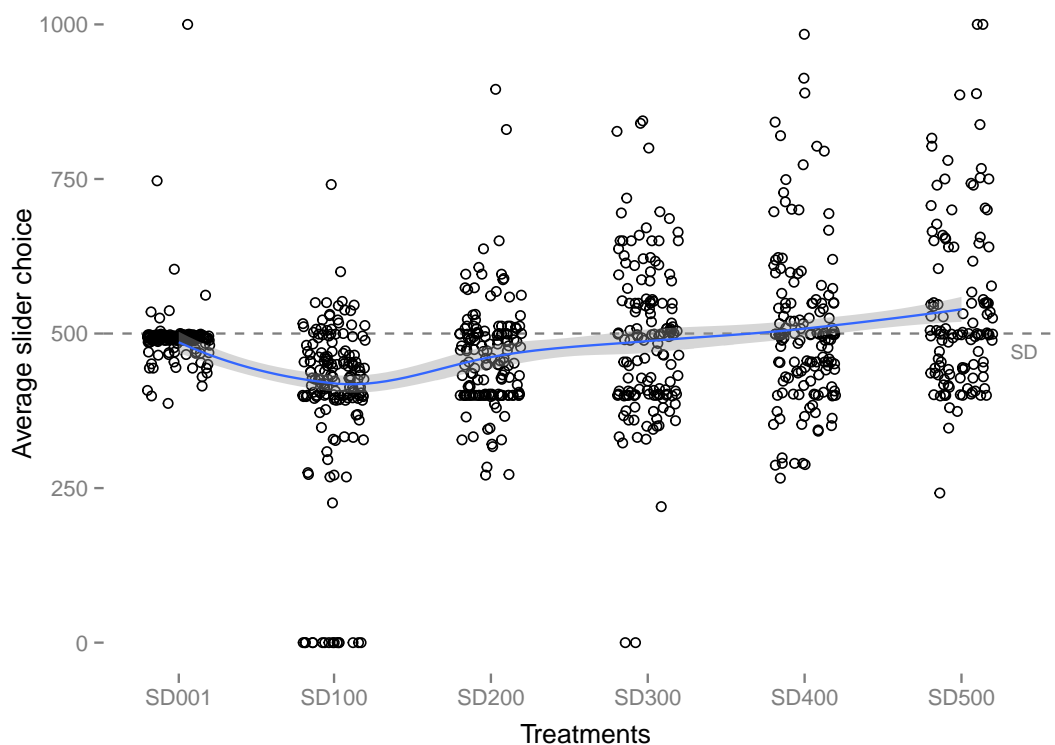
Hypothesis 1 holds that the relation between standard vagueness and activity choice designates a U-shape. In terms of our experiment, we predict that slider choices of participants will first decrease and then increase as treatments progress from SD001 to SD500. Figure 3 depicts the slider choices of each participant conditional on treatment and the smoothed conditional mean across treatments. In line with Hypothesis 1

<sup>10</sup> We programmed the experiment with z-Tree (Fischbacher, 2007) and we recruited participant with ORSEE (Greiner, 2015).

<sup>11</sup> Video instructions can be found via this link: <https://www.dropbox.com/sh/ebox9bgwr3kd4an/AABsUKtL44Ng4QI4aqtX19-la?dl=0>

the smoothed conditional mean in Figure 3 suggests a U-shaped relationship between increasing variability of the choice threshold and participants' average slider choice.

**Figure 3:** Individual average slider choice by treatment



**Note:** Observations are jittered horizontally to increase visibility.

To confirm the observation from Figure 3 we regress our treatment variable as linear term and as quadratic term on participants slider choice. As we have multiple responses per subject and thus need to resolve non-independence, we estimate the following mixed effects model with random intercepts:

$$\text{slider}_{ij} = \beta_{0j} + \beta_1 (SD_{ij}^2/100) + \beta_2 SD_{ij} + \epsilon_{ij}.$$

To properly center the estimation of the parabola, we deducted 250 from our treatment variable. Moreover, maximum-likelihood estimators can have problems when some predictor variables are much larger than others. As a precaution, we thus rescaled the quadratic treatment variable by dividing it by a constant.

Table 2 reports the results from the estimation. The positive and significant coefficient of the quadratic term (Likelihood Ratio test:  $\chi^2 = 2.839$ ,  $p = 0.092$ ) confirms the convexity observed in Figure 3. Moreover, the positive and significant coefficient of SD (Likelihood Ratio test:  $\chi^2 = 8.979$ ,  $p = 0.003$ ) indicates a slight positive linear trend. We

conclude that the second half of the U-shape is completed and that participants' slider choices at the highest level of variability are larger than at the lowest level of variability.

**Table 2:** Convexity of slider choice

	(Intercept)	SD <sup>2</sup> /100	SD
coefficient	460.517***	0.067*	0.181***
(st.error)	(14.899)	(0.040)	(0.060)

\*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ .

**Result 1 (U-shape):** With increasing variability of the choice threshold, participants' slider choices conform to a U-shape.

The results in Table 2 also inform the analysis of hypotheses 2. Hypothesis 2 holds that overcompliant behavior will emerge at low levels of standard vagueness. Given the parametrization in the experiment, the choice threshold under certainty is 500. This would also be the socially optimal amount derived as a benchmark from the theoretical model. Consequently, overcompliant choices are slider choices less than 500. In Table 2, the combination of convexity and the lower-than-500 intercept suggests that, on average, slider choices are lower than 500 (overcompliance) at lower levels of standard deviation.

To commence testing Hypothesis 2, we use a series of one-sample Wilcoxon signed-rank tests conditional on treatment. Table 3 reports the results. We reject the null hypothesis that the true location of the average slider choices is larger than or equal to 500 only for treatments SD001, SD100, and SD200. By contrast, average slider choices in SD300, SD400, and SD500 are not significantly below the 500-mark. Figure 3 illustrates that this result is not a mere artefact of a lack of observations in the overcompliance domain. As in SD300, SD400, and SD500 participants on average chose a slider position that was not significantly below the 500-mark, we conclude overcompliant behavior emerged at lower levels but not at higher levels of variability of the choice threshold.

**Table 3:** Overcompliance conditional on treatment

Treatment	Average choice	Test statistic (V)	P-value
SD001	492.56	59	0.004
SD100	393.86	5	< 0.000
SD200	461.89	34	0.003
SD300	487.76	124.5	0.239
SD400	504.17	150	0.506
SD500	540.32	139	0.899

**Note:** Results from one-sided, one-sample Wilcoxon signed-rank tests.

To extend the analysis of Hypothesis 2, we estimate treatment effects on slider choice

with a linear model. SD100 to SD500 enter the estimation as treatment dummies while SD001 is the reference treatment. As before, we resolve non-independence between within-subject observations by adding a random effect on the subject level. Model 1 in Table 4 reports the results. The simple model with treatment dummies and random intercepts at the participant level (model 1) shows that SD100 has a significant and substantial negative effect on the slider choice (Likelihood Ratio test:  $\chi^2 = 5.462$ ,  $p = 0.019$ ) relative to SD001. Participants' slider choice in treatments with higher variability was not significantly different from participants' slider choice in SD001. Relative to quasi-certainty in SD001, this result suggests overcompliance in SD100 but not in the other treatments. In a second estimation, we additionally control for risk preference, gain-loss preference, age, and gender (Table 4, Model 2).<sup>12</sup> While an increase of participants' risk attitude measure has a strong and significant negative effect on their slider choices (Likelihood Ratio test:  $\chi^2 = 9.806$ ,  $p = 0.002$ ), the negative effect of SD100 relative to SD001 remains significant (Likelihood Ratio test:  $\chi^2 = 4.093$ ,  $p = 0.043$ ). Neither the other control variables nor the treatments with higher variability have a significant effect on participants' slider choice. Thus after controlling for risk preference, gain-loss preference, age, and gender, the regression result is still consistent with Hypothesis 2: although standard vagueness steadily increases from SD001 to SD500, compared to SD001 only the low level of variability of the choice threshold in SD100 has a significant negative effect on participants' slider choice.

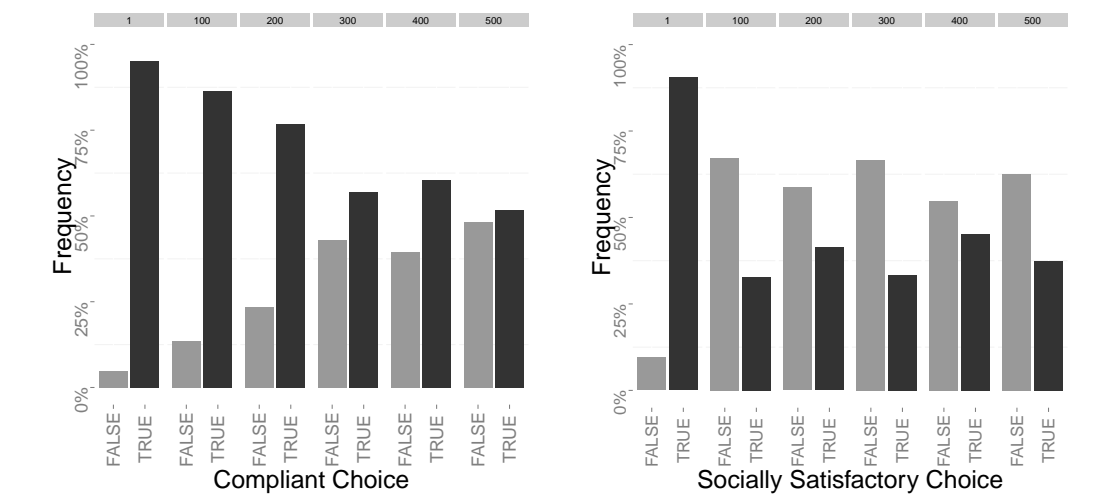
**Result 2 (overcompliance early):** After controlling for risk attitude, loss aversion, and gender, only SD100 has a significant negative effect on slider choices relative to SD001. The result signifies overcompliant choices in SD100.

As an additional analysis, we assign observed slider choices to one of two categories. First, we define slider choices below or equal to the social optimality benchmark of 500 as “compliant” and the rest as “non-compliant”. With this categorization we have socially optimal compliance in mind: if a regulator could set a precise and efficient standard, it would be at 500. We do not define these categories in relation to the choice threshold drawn in each round and for each single choice because its distribution varied across treatments and, therefore, the meaning of “compliant” would strongly differ between treatments. The left panel of Figure 4 illustrates the share of compliant and non-compliant choices across treatments. In SD001 the vast majority of choices were compliant (95.24%) and only a small fraction of activity level choices were non-compliant (4.76%). With the exception of SD300 and SD400, Figure 4 shows a steady decrease of the proportion of compliant choices. Simultaneously, the proportion of non-compliant choices increases from SD001 to SD300 and from SD400 to SD500. In SD500, only 51.67% of participants'

<sup>12</sup> Note that we could only introduce the controls (model 2 in Table 4) for a subset of the data. In sessions 1 and 4 of the experiment, right after the main task, we experienced technical problems with the computer infrastructure of the laboratory. Therefore, we could not elicit risk preferences and gain-loss preferences of the 35 participants in these sessions. We ran both estimations on the same subset of the data to increase comparability between the models.

slider choices were compliant and 48.33% of choices were non-compliant. As the shares of compliant and non-compliant choices appear to level out at SD300, we conduct a Fisher's exact test and we reject the null that the proportions of compliant choices are equal between SD001 and SD300 (odds ratio = 0.0667,  $p < 0.001$ ). At the same time, we do not reject the null that the proportions of compliant choices are equal between SD300 and SD500 (Fisher's exact test: odds ratio = 0.809,  $p = 0.457$ ).

**Figure 4:** Proportions of compliant and socially satisfactory choices



To analyze these findings in more detail, we estimate treatment effects on compliant choices with a probit model. As before, we include SD100 to SD500 as dummy variables relative to SD001. Risk attitude, loss aversion, age and gender serve as control variables and we cluster standard errors on the participant level. From the control variables, only our risk attitude measure has a significant and slightly positive effect on the probability of a compliant choice. All treatment variables have a significant negative effect. As probit coefficients are difficult to interpret, Table 4 reports average marginal effects (AMEs) calculated from the probit estimation. Average marginal effects range from  $-29.49\%$  in SD100 to  $-54.77\%$  in SD500. After conducting an overall Wald test ( $\chi^2 = 23.277$ ,  $p < 0.001$ ), we reject the null that the estimated coefficients of the probit model are equal across treatments. Specifically, the estimated negative effect is significantly stronger in SD300 compared to SD200 (Wald test:  $\chi^2 = 9.666$ ,  $p = 0.002$ ). In fact, all pairwise comparisons that include the step from SD200 to SD300 are also significant on the 1%-level, while the estimated coefficients of SD300, SD400, and SD500 are statistically indistinguishable. Therefore we conclude that SD300, SD400, and SD500 have significantly stronger negative effects than SD100 and SD200 on the probability that a participant makes a compliant choice.

**Result 3 (compliance crowding-out):** Relative to SD001 participants in all treatments are less likely to be compliant. This effect is significantly stronger in SD300,

SD400, and SD500 than in SD100 and SD200.

Second, we want to better understand the social impact of standard vagueness. To this end, we want to distinguish between those slider positions that approximate welfare maximisation and those that do not. Given the model parametrization, a precise and efficient choice threshold would be set at 500. Under these circumstances, a slider position of 500 would also be the individually optimal choice. To allow for some noise around the 500 benchmark, we use the standard deviation from observed slider choices in our quasi-legal-certainty treatment SD001 ( $\sigma_{SD001} = 49.62$ ). Across all treatments we then define those slider choices as “socially satisfactory” that lie within  $\sigma_{SD001}$  around 500. Slider choices with a larger absolute difference to 500 are “socially unsatisfactory”. We use this measure because SD001 resembles the control group of quasi-legal-certainty and the choices in SD001 are our best empirical benchmark for choice randomness absent choice threshold variability. Thus standard deviation of the choices in SD001 resembles the most narrow, yet least arbitrary criterion for our definition.

The right panel in Figure 4 reveals that the majority of choices in SD001 were socially satisfactory (90.48%), whereas only a small part was not (9.52%). By contrast, already in SD100 choices exhibit a drastic reversal: the share of socially satisfactory choices is much lower (32.74%) than the share of socially unsatisfactory choices (67.26%). We reject the null that the proportion of socially satisfactory versus socially unsatisfactory choices is equal between SD001 and SD100 (Fisher’s exact test: odds ratio = 0.052,  $p < 0.001$ ). Finally, only 37.50% of slider choices remain socially satisfactory in SD500 whereas 62.50% were not. We conduct a Fisher’s exact test and reject the null that the proportion of socially satisfactory versus socially unsatisfactory choices are equal between SD001 and SD500 (odds ratio = 0.064,  $p < 0.001$ ). However, a rejection is not possible when comparing the proportion of choices between SD100 and SD500 (Fisher’s exact test: odds ratio = 0.812,  $p = 0.452$ ). The evidence indicates that the proportion of socially satisfactory and unsatisfactory choices switches as soon as the variability of the choice threshold exceeds a quasi-certain level.

To further analyze this finding, we estimate effects on socially satisfactory choice with a probit model, using the same model specifications as the previous probit model for compliant choices. Similar to the estimation for compliant choices, among the control variables only our risk attitude measure has a significant and negative effect on the probability of a socially desirable slider choice. Compared to SD001, all treatments have a significant negative effect. Table 4 reports average marginal effects (AMEs) calculated from the probit estimation. Again similar to the previous estimation, all treatment variables have a significant negative average marginal effect, starting at  $-36.45\%$  in SD400 and increasing up to  $-43.86\%$  in SD300. In contrast to the analysis of compliant choices, however, we cannot reject the null that the negative treatment effect is equal across treatments (Wald test:  $\chi^2 = 2.165$ ,  $p = 0.705$ ). This result suggests that introducing variability of the choice threshold has a strong and significant negative effect on the probability that a slider choice is socially satisfactory, irrespective of how pronounced is the variability. We conclude that, given any degree of standard vagueness beyond

**Table 4:** Summary of regression analysis

	Slider choice		“compliant” choice	“socially satisfactory” choice
	Model 1	Model 2	(Probit AMEs)	(Probit AMEs)
SD100	-90.569** (39.414)	-77.513** (39.937)	-0.295*** (0.104)	-0.404*** (0.049)
SD200	-32.092 (41.337)	-23.502 (41.629)	-0.352*** (0.088)	-0.384*** (0.051)
SD300	2.215 (34.133)	-2.220 (33.855)	-0.516*** (0.057)	-0.439*** (0.048)
SD400	18.625 (34.133)	13.175 (33.336)	-0.493*** (0.063)	-0.365*** (0.050)
SD500	54.775 (35.253)	40.497 (34.859)	-0.548*** (0.068)	-0.416*** (0.045)
Risk Attitude		-19.414*** (6.372)	0.051*** (0.019)	-0.056 (0.021)
Loss Aversion		-0.030 (0.302)	0.001 (0.001)	0.000 (0.001)
Age		0.056 (2.571)	-0.003 (0.008)	-0.005 (0.007)
Female		15.906 (19.383)	-0.088 (0.060)	0.033 (0.059)
(Intercept)	485.542*** (27.870)	609.659*** (83.146)		

\*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ .

quasi-certainty, persons find it difficult to identify a socially satisfactory choice. We interpret this finding as loss of the coordination function of the standard.

**Result 4 (loss of coordination function):** All treatments except SD001 (quasi legal certainty) have a strong negative effect on the probability that a participant chooses a socially satisfactory slider position. This effect does not differ between these treatments.

## 5. Discussion

This paper provides laboratory evidence for the effect of standard vagueness on activity level choices. We use standard vagueness as but one variation of legal uncertainty. In general, the observations refute the explicit and implicit notion in doctrinal legal scholarship that legal uncertainty should be minimized where possible due to its stifling of socially beneficial activities (cf.: Trubek, 1972; D’Amato, 1983; Popelier, 2000; Maxeiner, 2007, 2008; Smits, 2012). Although we could capture the legal intuition in a framework of reference-dependent preferences, the results do not match that legal intuition. However,

the results clearly show that our participants were sensitive to the general presence and manipulation of standard vagueness. These results rather support earlier modelling efforts from the economic theory of law (Craswell and Calfee, 1986), as well as the notion that increases in legal uncertainty may necessarily not be socially disadvantageous.

The experimental evidence shows that a meaningful dynamic exists between activity choices and the degree of standard vagueness. The experiment does not reveal a monotonic negative relationship between standard vagueness and average slider choices, however. Rather, participants in this study responded non-monotonically to increases in standard vagueness. As a result, average slider choices exhibit a U-shape (Result 1). Participants were not only sensitive to the general presence of standard vagueness, but they differentiated between different vagueness levels and adopted non-monotonic responses. This finding suggests that intentionally reducing standard vagueness can result in unintended adverse consequences and undermine activity choices even further when standard vagueness is already high. Being concerned about different degrees of legal uncertainty—in contrast to treating a fixed level of legal uncertainty as a working hypothesis—is, therefore, relevant for finding appropriate legal solutions. To the detriment of individuals and society, different degrees of legal uncertainty can lead to adverse choices of rule-subjected persons.

Moreover, participants did not consistently choose inefficiently low slider positions. Only initial levels of standard vagueness (SD001, SD100, and SD200) induced significant overcompliant behavior (Result 2). Whereas one may expect low standard vagueness to only cause insignificant overcompliance, overcompliance was much more pronounced at low standard variability than at high standard variability. Activity choices dropped quickly when the random choice threshold became less predictable. Interestingly, however, statistically meaningful overcompliant behavior vanished already by SD300.

Altogether our results correspond to previous contributions suggesting that increasing legal uncertainty can have beneficial effects (Craswell and Calfee, 1986; Lang, 2014). Thus, the experimental evidence from our study suggests that the doctrinal view is warranted only when a rule designer confronts a choice between very low levels of legal uncertainty where activity choices on average erode with increasing legal uncertainty. Adopting a lower degree of legal uncertainty when legal uncertainty is already substantial may increase overcompliance. Conversely, increasing standard vagueness may lead to a socially desirable change in terms of average activity choices. If reducing legal uncertainty is costly, these counter-intuitive implications attain even more weight.

In addition, the experimental evidence reveals effects that have previously received little attention. First, the analysis shows that increasing legal uncertainty gradually decreases the proportions of compliant choices (Result 3). Under legal uncertainty, compliance is crowded-out. Second, the main share of participants' choices is not socially satisfactory as soon as more than minimal levels of legal uncertainty are induced in the experiment (Result 4). This result suggests that another hidden cost of legal uncertainty manifests in increasingly erratic behavior: the rule loses its coordination function. To the best of our knowledge the discussion on legal uncertainty has not focused on this aspect, let alone backed-up such discussion by empirical results. The erosion of the coordination



function of the law is an important finding because it affects the cost to society in anticipation of a certain individual activity choice. Such costs include the excessive or insufficient purchase of insurance and other investments to forego harm. Although the direct results of the experiment refute much of the legal intuition on legal uncertainty, both the crowding-out of compliant choices and the undermining of socially satisfactory choices reinvigorates the motivation to minimize legal uncertainty where possible. While the data suggest that an incremental reduction of standard vagueness from higher to lower levels facilitates compliant choices, stimulating socially satisfactory choices would require reducing standard vagueness to quasi legal certainty. This, however, is a tall order.

## **6. Conclusion**

Legal scholars and economists disagree about the effects of legal uncertainty on a person's activity choice. Legal scholars argue that introducing or increasing legal uncertainty erode socially beneficial activities, whereas economists, counter-intuitively, propose that doing so may have beneficial effects under specific circumstances. We show that a model of activity choice under a vague legal standard can accommodate both views depending on the assumptions about a person's preference structure.

Our laboratory experiment studies how different degrees of standard vagueness impact activity choice by varying the dispersion of the distribution underlying the vague standard. The data from our experiment show that initial degrees of standard vagueness reduce average activity choices below the socially optimal level. After a sufficient increase of standard vagueness, however, participants' choices become less overcompliant. After a further increase, overcompliance vanishes. The data further reveal that both the share of non-compliant choices and the share of socially undesirable choices substantially increase with increasing degrees of standard vagueness. With increasing vagueness the standard loses its coordination function.

To the extent that our results apply to real-world settings, they have important policy implications. Whereas legal scholars often conceive of legal uncertainty as impairment of activity choice, our results suggest that, on average, reducing legal uncertainty may cause more harm than good. On the contrary, increasing legal uncertainty may sometimes be socially beneficial. We do not propose to design rules with a specific optimal degree of vagueness, however. We merely emphasize that the immediate urge to reduce, e.g., standard vagueness may be misguided, especially when such a policy generates substantial additional cost and when some amount of legal uncertainty is inherent in the law. Yet, whereas increasing legal uncertainty may on average not be socially detrimental, with increasing vagueness the law loses its coordination function. Therefore, our results draw attention to the need to shift the discussion about legal uncertainty from its average effects to the predictability of individual behavior under different degrees of legal uncertainty and the consequences thereof. As our laboratory study implemented a vague legal standard, we refrain from drawing conclusions for forms of legal uncertainty different from standard vagueness.

Forms of legal uncertainty different from standard vagueness, however, are interesting avenues for further research. For example, legal uncertainty may concern outcomes such as compensatory or punitive damage awards. Moreover, changes in procedural or evidentiary rules may bias the distribution underlying the legal standard. Promising opportunities for future research also exist within our paradigm. Our contribution provides both a foundation and a benchmark to study, for example, the interaction of vague standards with social preferences. Tortious actions can happen in different social contexts: under vague standards, a car driver facing a potential traffic accident with a stranger may adjust his activity differently than a physician treating a long-term patient that she knows well. Another interesting extension of our study asks to what extent gain-loss framing effects interact with different degrees of standard vagueness. Finally, while we experimentally test legal uncertainty inherent in legal rules, some may conclude from our results that legal uncertainty may be employed as policy tool. We do not yet understand, however, how legal uncertainty impacts individual behavior when persons realize that they are exposed to legal uncertainty by design.

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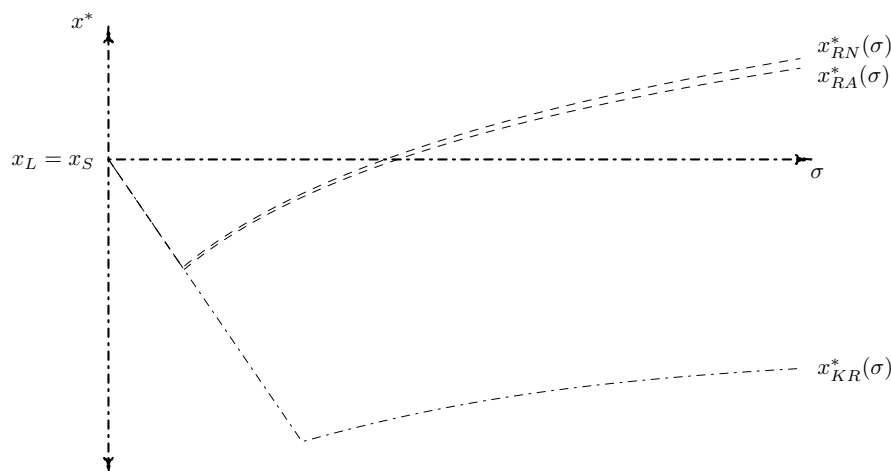
## Appendix A.

As robustness check, we have simulated the optimal responses  $x_i^*(\sigma)$ ,  $i \in \{RN, RA, KR\}$ , when  $x_L$  is not normally but uniformly distributed around the socially optimal level  $x_S$ . To incorporate the notion of standard vagueness, we have defined  $x_L \sim \mathcal{U}(x_S - 1.25\sigma, x_S + 1.25\sigma)$ . Figure 5 depicts the results. The emerging pattern shows defining features comparable with the pattern under a normal distribution. Therefore our predictions would not change qualitatively if the legal threshold was uniformly distributed.

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**Figure 5:** Over- and undercompliance with uniformly distributed  $x_L$

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## Appendix B.

Craswell and Calfee (1986) propose in their Appendix A that a person maximizes  $U_{CC}(x) = u(b(x)) - F(x)u(e(x))$ , where  $u'(\cdot) > 0$ ,  $u''(\cdot) < 0$  (Craswell and Calfee, 1986,

p. 300). Reverse-engineering an expected utility expression with a complete probability space from the latter maximization problem yields

$$\begin{aligned} U_{CC}(x) &= u(b(x)) - F(x) u(e(x)) \\ &= (1 - F(x)) u(b(x)) + F(x) u(b(x)) - F(x) u(e(x)) \\ &= (1 - F(x)) u(b(x)) + F(x) (u(b(x)) - u(e(x))). \end{aligned} \quad (10)$$

Therefore the underlying utility function of Craswell and Calfee (1986)'s risk-averse agent is

$$u_{CC}(x) = \begin{cases} u(b(x)) & \text{for } x \leq x_L \text{ (compliance)} \\ u(b(x)) - u(e(x)) & \text{for } x > x_L \text{ (violation)} \end{cases}.$$

The crucial difference between the utility functions  $u_{RA}(\cdot)$  in expression (5) and  $u_{CC}(\cdot)$  lies in how a person evaluates outcomes of choices that are potentially violating the legal standard ( $x > x_L$ ). Under  $u_{RA}(\cdot)$  a person first computes final wealth and then evaluates this outcome through his utility function (asset integration), i.e.,  $u(b(x) - e(x))$  for  $x > x_L$ . Conversely, under  $u_{CC}(\cdot)$  a person separates these different payoff streams and in an isolated way computes the utility for each of the payoffs (asset isolation), i.e.,  $u(b(x)) - u(e(x))$  for  $x > x_L$ . This difference concerns a crucial assumption about how a person edits or codes lottery outcomes (Kahneman and Tversky, 1979; Thaler, 1985; Read, Loewenstein, and Rabin, 1999). The hedonic consequences of the decision then depend on which editing procedure is used (cf.: Wakker, 2010, p. 235-236).

The assumption of asset isolation implicitly found its way into Craswell and Calfee (1986)'s analysis and has substantial consequences for predictions about a person's choices under vague standards. Differentiating expression (10) with respect to  $x$  and evaluating the result at the socially optimal level  $x_S$ , where  $b'(x) = e'(x)$ , yields

$$\left. \frac{\partial U_{CC}(x)}{\partial x} \right|_{x_S} = [1 - F(x_S) \frac{u'(e(x_S))}{u'(b(x_S))}] u'(b(x_S)) b'(x_S) - F'(x_S) u(e(x_S)). \quad (11)$$

Note that the marginal benefits of increasing  $x$  are not only discounted by the probability  $1 - F(x_S)$  as in the main text, but rather by  $1 - F(x_S) u'(e(x_S))/u'(b(x_S))$ . Because we evaluate the decision locally at  $x_S$ , we can reformulate the additional factor  $u'(e(x_S))/u'(b(x_S))$  to

$$\frac{u'(e(x_S))}{u'(b(x_S))} = \frac{u'(e(x_S))}{u'(b(x_S))} \frac{b'(x_S)}{b'(x_S)} = \frac{u'(e(x_S))}{u'(b(x_S))} \frac{e'(x_S)}{b'(x_S)} = \theta.$$

Parameter  $\theta$  may be interpreted as marginal rate of substitution between  $u(e(x))$  and  $u(b(x))$ , i.e., the local rate at which a person is willing to compensate for the negative externality of activity  $x$  in exchange for receiving the private benefits of said activity while maintaining the same level of total utility. If  $\theta > 1$ , then  $1 - F(x_S) \theta < 1 - F(x_S)$ . With risk aversion and asset isolation as in (11), marginal benefits of increasing  $x$  are

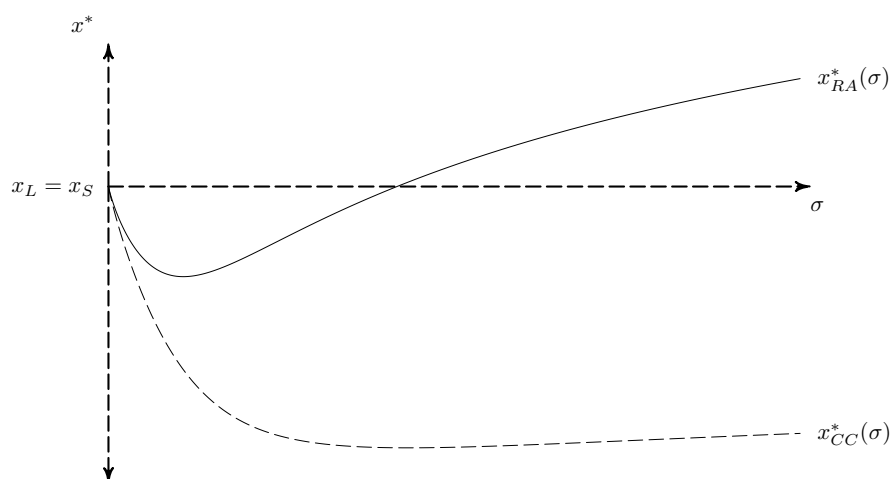
discounted more than with risk aversion and asset integration in (6). Therefore, iff  $\theta > 1$  the first term of expression (11) is smaller than the first term in expression (6). This case creates a stronger tendency to choose  $x^* > x_S$  (undercompliance). By contrast, iff  $\theta < 1$  then  $1 - F(x_S) \theta > 1 - F(x_S)$ , i.e., marginal utility of increasing  $x$  would be discounted less under asset isolation. Therefore, iff  $\theta < 1$  the first term of expression (11) is larger than the first term in expression (6). This case creates a stronger tendency to choose  $x^* < x_S$  (overcompliance). Altogether, a person who edits outcomes according to asset isolation is more likely to deviate from  $x_S$  when the legal standard somewhat random.

To illustrate the stark contrast caused by assuming asset isolation in lieu of asset integration, we simulate the distinctive response function  $x_{CC}^*(\sigma)$  (asset isolation) and compare it to  $x_{RA}^*(\sigma)$  (asset integration) in Figure 6. Instead of a transition from overcompliance at lower degrees of vagueness to undercompliance at higher degrees of vagueness,  $x_{CC}^*(\sigma)$  exhibits a rapid drop over the entire range of  $\sigma$  so that  $x_{CC}^*(\sigma) < x_{RA}^*(\sigma)$ . This pattern signifies extensive overcompliance. That is, assuming asset isolation in addition to risk aversion also supports the legal scholarship view on legal uncertainty.

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**Figure 6:** Asset Integration vs. Asset Integration

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## Appendix C.

For the generation of the hypotheses, for the simulation of the different response functions, and for the payoff structure in the experiment, the following specifications for  $b(x)$  and  $e(x)$  hold:

$$b(x) = 50 \ln(x)$$
$$e(x) = 0.1 x$$

These specifications come from Craswell and Calfee (1986)'s first example (Craswell and Calfee, 1986, p. 284).

As functional form capturing absolute utility components, we use an utility function with constant relative risk aversion (CRRA); specifically, an utility function from the power family  $u(w) = w^r$ . Utility functions of this form have been widely used for modelling risk aversion, both in economics and psychology, and often better fit empirical results than alternative functional forms (Wakker, 2008). We parametrized the curvature parameter with  $r = 0.48$  in accordance with the recent estimate of Gneezy, Imas, and List (2015). We prefer the estimate from this elicitation mechanism because risk attitude is domain specific and Gneezy, Imas, and List (2015)'s elicitation is based on lottery choices similar to our experiment. Moreover, in the experiment we use a similar elicitation procedure to estimate and control for risk preferences.

Moreover, we parametrize loss aversion with  $\lambda = 2.61$  in accordance with the estimation of Abdellaoui, Bleichrodt, and L'Haridon (2008, p. 258). Their elicitation method strikes a balance between non-parametric measurements and susceptibility to response error and provides an advantage in measurement efficiency. Moreover, the elicitation mechanism uses only those parametric assumptions that are widely supported in the literature, i.e., the power specification for utility that we also used to model the curvature of the utility functions. The method is also perceived to be easier than other methods and minimizes cognitive burden for participants which leads to high reliability. Finally, the method is robust because elicited measurements do not depend on specific probability values. In this regard, the measurements are unconfounded. Abdellaoui, Bleichrodt, and L'Haridon (2008) also found no gender effect in the estimation of loss aversion with their procedure.

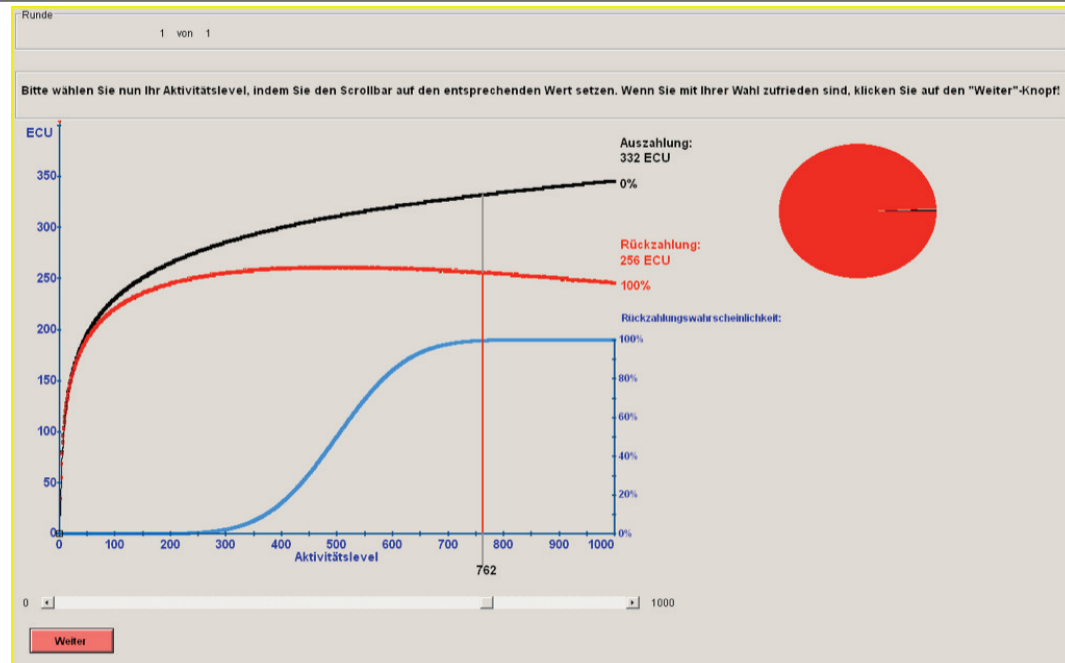
Note finally that we did not find a fundamental change in the prediction pattern that results from the simulations depicted in Figure 1, even when substantially altering the parametrization.

## Appendix D.

The following figure contains an example of a participants decision screen in treatment SD100. The screen shows the pure payoff function  $b(x)$  from the chosen activity level, the reduced payoff function  $b(x) - e(x)$ , and a cumulative distribution function that determines the probability of exceeding the randomly determined activity benchmark. On this screen, the slider position is set to 762. The screen conveniently depicts potential payoffs in ECU with their corresponding probabilities for this slider position. Because people are commonly found to struggle with the meaning of specific probabilities, the pie chart next to the payoffs makes more salient the meaning of the probabilities.



Figure 7: Sample Screen of the Decision Screen in the Experiment



## Referee Appendix (not intended for publication).

This referee appendix is not supposed to be published. It is intended to make traceable the formal analysis in the paper. Thus the referee appendix facilitates refereeing the paper by providing a clear step-by-step computation of the mathematical expressions used in the paper.

### I. Details for Section 2.1

The expected utility formula for  $U_{RN}(x)$  in expression (2) computes as follows:

$$\begin{aligned}
 U_{RN}(x) &= (1 - F(x)) b(x) + F(x) (b(x) - e(x)) \\
 &= (1 - F(x)) b(x) + F(x) b(x) - F(x) e(x) \\
 &= b(x) - F(x) e(x).
 \end{aligned}$$

Differentiating  $U_{RN}(x)$  with respect to  $x$  yields:

$$\begin{aligned}\frac{\partial U_{RN}(x)}{\partial x} &= b'(x) - [F'(x) e(x) + F(x) e'(x)] \\ &= b'(x) - F'(x) e(x) - F(x) e'(x).\end{aligned}$$

Using the condition  $b'(x) = e'(x)$  when evaluating the agents incentives at the socially optimal level  $x_S$ , the expression simplifies to:

$$\begin{aligned}\left. \frac{\partial U_{RN}(x)}{\partial x} \right|_{x_S} &= b'(x_S) - F'(x_S) e(x_S) - F(x_S) b'(x_S) \\ &= (1 - F(x_S)) b'(x_S) - F'(x_S) e(x_S).\end{aligned}$$

This expression corresponds to (4) in the main text.

## II. Details for Section 2.2

Expected utility following from expression (5) is

$$U_{RA}(x) = (1 - F(x)) u(b(x)) + F(x) u(b(x) - e(x)).$$

Expanding the first term of  $U_{RA}(x)$  and differentiating the ensuing expression leads to:

$$\begin{aligned}\frac{\partial U_{RA}(x)}{\partial x} &= u'(b(x)) b'(x) \\ &\quad - F'(x) u(b(x)) - F(x) u'(b(x)) b'(x) \\ &\quad + F'(x) u(b(x) - e(x)) + F(x) u'(b(x) - e(x)) (b'(x) - e'(x)) \\ &= (1 - F(x)) u'(b(x)) b'(x) \\ &\quad - F'(x) [u(b(x)) - u(b(x) - e(x))] \\ &\quad + F(x) u'(b(x) - e(x)) (b'(x) - e'(x))\end{aligned}$$

When plugging in condition  $b'(x) = e'(x)$  to evaluate a person's incentives at the socially optimal level  $x_S$ , this expression simplifies to:

$$\begin{aligned}
 \left. \frac{\partial U_{RA}(x)}{\partial x} \right|_{x_S} &= (1 - F(x_S)) u'(b(x_S)) b'(x_S) \\
 &\quad - F'(x_S) [u(b(x_S)) + u(b(x_S) - e(x_S))] \\
 &\quad + F(x_S) u'(b(x_S) - e(x_S)) (b'(x_S) - b'(x_S)) \\
 &= (1 - F(x_S)) u'(b(x_S)) b'(x_S) \\
 &\quad - F'(x_S) [u(b(x_S)) - u(b(x_S) - e(x_S))]
 \end{aligned}$$

as the third term becomes zero. This is expression (6) in the main text.

### III. Details for Section 2.3

If a court finds  $x \leq x_L$ , the agent receives  $b(x)$  as final wealth. The alternative outcome  $b(x) - e(x)$  occurs with probability  $F(x)$ . In this case, her expectation-based reference-dependent utility is

$$\begin{aligned}
 u_{KR}(x) \Big|_{x \leq x_L} &= m(b(x)) + F(x) \mu(b(x) - (b(x) - e(x))) \\
 &= m(b(x)) + F(x) \mu(b(x) - b(x) + e(x)) \\
 &= m(b(x)) + F(x) \mu(e(x)) \\
 &= m(b(x)) + F(x) m(e(x)).
 \end{aligned}$$

This expression corresponds to the case  $x \leq x_L$  in expression (8). Intuitively, a person derives absolute utility from obtaining income  $b(x)$  and from a gain of  $e(x)$  compared to the alternative outcome  $r_{x > x_L} = b(x) - e(x)$  that is discounted by its likelihood.

If a court finds  $x > x_L$ , the agent receives  $b(x) - e(x)$  as final wealth. The alternative outcome  $b(x)$  occurs with probability  $1 - F(x)$ . In this case, her reference-dependent utility is

$$\begin{aligned}
 u_{KR}(x) \Big|_{x > x_L} &= m(b(x) - e(x)) + (1 - F(x)) \mu(b(x) - e(x) - b(x)) \\
 &= m(b(x) - e(x)) + (1 - F(x)) \mu(-e(x)) \\
 &= m(b(x) - e(x)) + (1 - F(x)) (-\lambda) m(-(-e(x))) \\
 &= m(b(x) - e(x)) - \lambda (1 - F(x)) m(e(x)).
 \end{aligned}$$

This expression corresponds to the case  $x > x_L$  in expression (8). Intuitively, a person derives absolute utility from obtaining income  $b(x) - e(x)$  and from a loss of  $e(x)$  compared to the alternative outcome  $r_{x \leq x_L} = b(x)$  that is discounted by its likelihood but also weighted by the loss aversion parameter  $\lambda$ . Her expected expectation-based reference-dependent utility is

$$\begin{aligned}
 U_{KR}(x) &= (1 - F(x)) [m(b(x)) + F(x) m(e(x))] \\
 &\quad + F(x) [m(b(x) - e(x)) - \lambda (1 - F(x)) m(e(x))] \\
 &= (1 - F(x)) m(b(x)) \\
 &\quad + (1 - F(x)) F(x) m(e(x)) \\
 &\quad + F(x) m(b(x) - e(x)) \\
 &\quad - \lambda F(x) (1 - F(x)) m(e(x)).
 \end{aligned}$$

Differentiating this expression with respect to  $x$  yields

$$\begin{aligned}
 \frac{\partial U_{KR}(x)}{\partial x} &= (1 - F(x)) m'(b(x)) b'(x) - F'(x) m(b(x)) \\
 &\quad + (1 - F(x)) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] - F(x) F'(x) m(e(x)) \\
 &\quad + F(x) m'(b(x) - e(x)) (b'(x) - e'(x)) + F'(x) m(b(x) - e(x)) \\
 &\quad - \lambda [(1 - F(x)) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] - F(x) F'(x) m(e(x))] \\
 &= (1 - F(x)) m'(b(x)) b'(x) - F'(x) m(b(x)) \\
 &\quad + (1 - F(x)) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] - \lambda (1 - F(x)) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] \\
 &\quad + F(x) m'(b(x) - e(x)) (b'(x) - e'(x)) + F'(x) m(b(x) - e(x)) \\
 &\quad + \lambda F(x) F'(x) m(e(x)) - F(x) F'(x) m(e(x)) \\
 &= (1 - F(x)) m'(b(x)) b'(x) - F'(x) m(b(x)) \\
 &\quad + (1 - \lambda) (1 - F(x)) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] \\
 &\quad + F(x) m'(b(x) - e(x)) (b'(x) - e'(x)) + F'(x) m(b(x) - e(x)) \\
 &\quad + (\lambda - 1) F(x) F'(x) m(e(x))
 \end{aligned}$$

Some further reformulation gets

$$\begin{aligned}
 \frac{\partial U_{KR}(x)}{\partial x} &= (1 - F(x)) m'(b(x)) b'(x) - F'(x) m(b(x)) \\
 &\quad - (1 - F(x)) (\lambda - 1) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] \\
 &\quad + F(x) m'(b(x) - e(x)) (b'(x) - e'(x)) + F'(x) m(b(x) - e(x)) \\
 &\quad + F'(x) (\lambda - 1) F(x) m(e(x)) \\
 &= (1 - F(x)) m'(b(x)) b'(x) \\
 &\quad - F'(x) m(b(x)) + F'(x) m(b(x) - e(x)) \\
 &\quad - (1 - F(x)) (\lambda - 1) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] \\
 &\quad + F'(x) (\lambda - 1) F(x) m(e(x)) \\
 &\quad + F(x) m'(b(x) - e(x)) (b'(x) - e'(x)) \\
 &= (1 - F(x)) \left[ m'(b(x)) b'(x) - (\lambda - 1) [F'(x) m(e(x)) + F(x) m'(e(x)) e'(x)] \right] \\
 &\quad - F'(x) \left[ m(b(x)) - m(b(x) - e(x)) - (\lambda - 1) F(x) m(e(x)) \right] \\
 &\quad + F(x) m'(b(x) - e(x)) (b'(x) - e'(x))
 \end{aligned}$$

Evaluating a person's incentives at the socially optimal level  $x_S$  and can plugging in  $b'(x) = e'(x)$ , the last term collapses to zero and we obtain

$$\begin{aligned}
 \frac{\partial U_{KR}(x)}{\partial x} \Big|_{x_S} &= (1 - F(x_S)) m'(b(x_S)) b'(x_S) \\
 &\quad - (1 - F(x_S)) (\lambda - 1) [F'(x_S) m(e(x_S)) + F(x_S) m'(e(x_S)) e'(x_S)] \\
 &\quad - F'(x_S) [m(b(x_S)) - m(b(x_S) - e(x_S))] \\
 &\quad + F'(x_S) (\lambda - 1) F(x_S) m(e(x_S))
 \end{aligned}$$

The latter expression corresponds to (9) in the main text.