Risk Preference and Risk Type: Aggregating Data from Multiple Domains[*]

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I. Introduction

What is your tolerance for risk? How risky are you?

There is a large body of research in economics and related fields that uses field data from a single context or domain to endeavor to understand people's risk preferences and risk types. In studying people's risk preferences, researchers have examined, for example, their insurance choices,[1] investment decisions,[2] labor supply decisions,[3] and gambling behavior at racetracks,[4] on game shows,[5] and online.[6]

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[1] *See, e.g.*, Charles J. Cicchetti & Jeffrey A. Dubin, *A Microeconometric Analysis of Risk Aversion and the Decision to Self-Insure*, 102 J. POL. ECON. 169 (1994) (interior telephone wire insurance); Alma Cohen & Liran Einav, *Estimating Risk Preferences from Deductible Choice*, 97 AM. ECON. REV. 745 (2007) (auto insurance); Justin Sydnor, *(Over)insuring Modest Risks*, 2 AM. ECON. J. APPLIED ECON. 177 (2010) (home insurance).

[2] *See, e.g.*, Daniel Paravisini et al., *Risk Aversion and Wealth: Evidence from Person-to-Person Lending Portfolios*, Social Science Research Network Working Paper No. 1507902 (Jan. 14, 2013). Available at http://ssrn.com/abstract=1507902.

[3] *See* Raj Chetty, *A New Method of Estimating Risk Aversion*, 96 AM. ECON. REV. 1821 (2006).

[4] *See, e.g.*, Bruno Jullien & Bernard Salanié, *Estimating Preferences under Risk: The Case of Racetrack Bettors*, 108 J. POL. ECON. 503 (2000); Erik Snowberg & Justin Wolfers, *Explaining the Favorite-Longshot Bias: Is It Risk-Love or Misperceptions?*, 118 J. POL. ECON. 723 (2010).

[5] *See, e.g.*, Robert Gertner, *Game Shows and Economic Behavior: Risk-Taking on "Card Sharks,"* 108 Q. J. ECON. 507 (1993); Andrew Metrick, *A Natural Experiment in Jeopardy!*, 85 AM. ECON. REV. 240 (1995); Thierry Post et al., *Deal or No Deal? Decision Making under Risk in a Large-Payoff Game Show*, 98 AM. ECON. REV. 38 (2008).

[6] *See, e.g.*, Angie Andrikogiannopoulou & Filippos Papakonstantinou, *Estimating Heterogeneous Risk Preferences from a Panel of Real-World Betting Choices*, Swiss Finance Institute Research Paper No. 13-53 (Sept. 1, 2013). Available at http://ssrn.com/abstract=2239194.

In studying people's risk types, researchers have examined, for example, their propensity for insurance claims,[7] financial default,[8] absenteeism,[9] criminality,[10] and job turnover.[11]

Building upon this "single domain" literature, there is a growing body of research that aggregates data from multiple contexts or domains. These studies use field data that record, for each unit of observation (typically an individual or household), the unit's risky choices or risky outcomes in several (often closely related) contexts or domains. To my mind, multiple domain data equals big data. With multiple domain data, researchers not only can investigate the nature of people's risk preferences and risk types within a particular context or domain, they also can investigate the extent to which their risk preferences and risk types are context-specific versus domain-general. To the extent people's risk preferences and risk types are domain-general, researchers (or corporations or governments) can use their behavior in one risky context to learn and make predictions about their behavior in other contexts.

This chapter surveys three papers in this nascent "multiple domain" literature. Section II reviews two published studies on risk preference. Section III then discusses one unpublished study on risk type. Finally, Section IV draws preliminary conclusions and extols the promise of multiple domain research, for social science and evidence-based policy making.

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[7] *See generally* MICHEL DENUIT ET AL., ACTUARIAL MODELLING OF CLAIM COUNTS: RISK CLASSIFICATION, CREDIBILITY, AND BONUS-MALUS SYSTEMS (2007).

[8] *See, e.g.*, David B. Gross & Nicholas S. Souleles, *An Empirical Analysis of Person Bankruptcy and Delinquency*, 15 REV. FIN. STUD. 319 (2002); Scott Fay et al., *The Household Bankruptcy Decision*, 92 AM. ECON. REV. 706 (2002); Luigi Guiso et al., *The Determinants of Attitudes towards Strategic Default on Mortgages*, 68 J. FIN. 1473 (2013).

[9] *See, e.g.*, Simen Markussen et al., *The Anatomy of Absenteeism*, 30 J. HEALTH ECON. 277 (2011).

[10] *See, e.g.*, Naci Mocan & Erdal Tekin, *Ugly Criminals*, 92 REV. ECON. & STAT. 15 (2010).

[11] *See, e.g.*, John L. Cotton & Jeffrey M. Tuttle, *Employee Turnover: A Meta-Analysis and Review with Implications for Research*, 11 ACAD. MGMT. REV. 55 (1986); Rodger W. Griffeth et al., *A Meta-Analysis of Antecedents and Correlates of Employee Turnover: Update, Moderator Tests, and Research Implications for the Next Millennium*, 26 J. MGMT. 463 (2000).

II. Two Studies on Risk Preference

A. Are Risk Preferences Stable across Contexts? Evidence from Insurance Data

In an article published in the *American Economic Review* in 2011, Levon Barseghyan et al. investigate the empirical validity of the standard assumption in economics that people's risk preferences are stable across decision contexts.[12] The authors assemble a dataset that records the insurance choices of 702 households in three lines of coverage: auto collision, auto comprehensive, and home all perils.[13] They use the data to test whether the households' deductible choices across coverage lines reflect the same degree of absolute risk aversion.[14] The test relies on a model of deductible choice which assumes, inter alia, that households are expected utility maximizers and that households know their coverage-specific claim rates (i.e., the average rate at which they will experience claims in each line of coverage).

Under the assumptions of the model, Barseghyan et al. derive an expression for the coefficient of absolute risk aversion at which a household is indifferent between any two deductible options. This indifference point is a function of the deductible options, the associated premiums, and the household's claim rate.[15] The authors' test leverages the idea that each deductible choice by a household implies that its coefficient of absolute risk aversion lies between two indifference points. For example, if the

[12] Levon Barseghyan et al., *Are Risk Preferences Stable across Contexts? Evidence from Insurance Data*, 101 AM. ECON. REV. 591 (2011).

[13] Auto collision coverage pays for damage to the insured vehicle caused by a collision with another vehicle or object, without regard to fault. Auto comprehensive coverage pays for damage to the insured vehicle from all other causes (e.g., theft, fire, flood, windstorm, glass breakage, vandalism, hitting or being hit by an animal or by falling or flying objects), without regard to fault. Home all perils coverage pays for damage to the insured home from all causes (e.g., fire, windstorm, hail, tornadoes, vandalism, or smoke damage), except those that are specifically excluded (e.g., flood, earthquake, or war).

[14] The degree or coefficient of absolute risk aversion is defined as $r = -u''(w)/u'(w)$, where $u(\cdot)$ is the household's utility function and w is the household's wealth. *See, e.g.*, ANDREU MAS-COLELL ET AL., MICROECONOMIC THEORY 190 (1995).

[15] Although the deductible options and associated premiums are observable variables, the household's claim rate is a latent variable. The authors use data on claim realizations and demographics to estimate the household's claim rate. More specifically, they estimate the relationship in the data between the households' claim counts and their observable characteristics and use the estimates to predict the latent claim rate for each household.

household chooses a deductible of $250 from a menu of $100, $250, and $500, then the indifference point between $250 and $500 provides a lower bound on its coefficient of absolute risk aversion and the indifference point between $100 and $250 provides an upper bound. In this fashion, a household's deductible choice in each line of coverage identifies an interval that must contain its coefficient of absolute risk aversion. Because a household makes deductible choices in three lines of coverage—auto collision, auto comprehensive, and home all perils—its choices imply three intervals. The authors' test simply asks whether the intervals intersect. If the intervals intersect, then any coefficient of absolute risk aversion contained in the intersection can rationalize the household's choices. If the intervals do not intersect, however, then the household's choices cannot be rationalized by the same coefficient of absolute risk aversion.

Barseghyan et al. find that the hypothesis of stable risk preferences is rejected by the data. More specifically, they find that only 23 percent of households "pass" the test—i.e., the three intervals intersect for only 23 percent of households. This is quite low considering that the pass rate would be 14 percent if households were randomly assigned their deductible choices.[16] As for the other 77 percent, the authors find that these households typically exhibit greater risk aversion in their home deductible choices than they do in their auto deductible choices. In the home domain, the average household would pay $45 to avoid facing a gamble offering an equal chance of winning and losing $100. In the auto domain, by comparison, the average household would pay only $30 to avoid facing the same gamble.

To further illustrate their results, the authors compare the joint distribution of auto collision and home deductibles in the data with the joint distribution generated by the model under the null

[16] That said, even if every household had stable risk preferences, one should not expect a pass rate of 100 percent. This is because the households' true claim rates are bound to differ from their predicted claim rates due to unobserved heterogeneity. Therefore, as a relevant point of comparison, the authors simulate the expected pass rate under the null hypothesis of stable risk preferences. They find that the expected pass rate is 50 percent, more than twice the actual percentage.

hypothesis of stable risk preferences—see Figure 1. Conditional on their auto collision deductibles, the model predicts that households would choose "high" home deductibles ($500 or higher) with significantly greater frequency than is observed in the data.[17] Because lower deductibles correspond to more insurance, the figure illustrates not only the conclusion that the hypothesis of stable risk preferences is rejected by the data, but also the finding that households exhibit greater risk aversion in the home domain than they do in the auto domain.

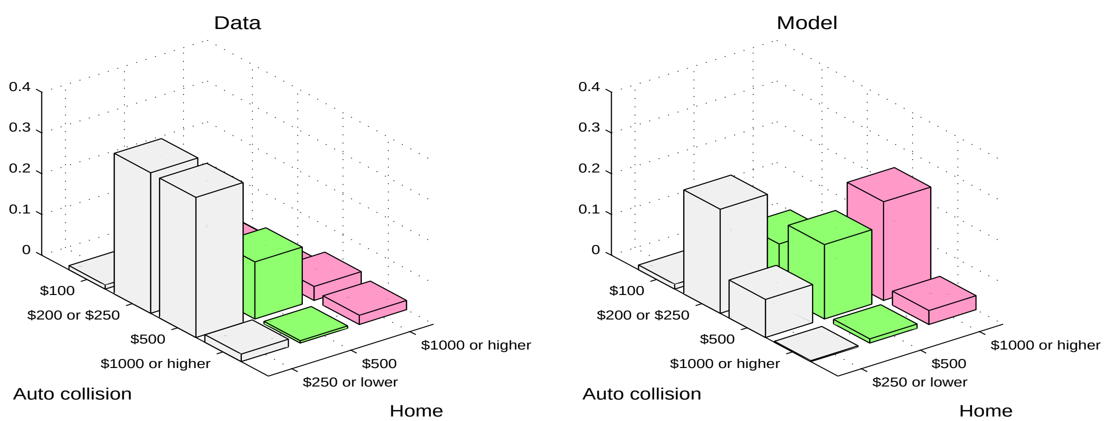

Figure 1: Empirical versus Model-Generated Joint Distribution of Auto Collision and Home Deductibles[18]

In their concluding remarks, Barseghyan et al. discuss several potential explanations for their results, including the possibility that people have systematic risk misperceptions, a topic which they explore in subsequent research.[19] They also acknowledge that rejecting the hypothesis of stable risk preference is not equivalent to rejecting the hypothesis that there is no domain-general component to

[17] Indeed, the authors report that a Wald test rejects at the 1 percent level the equality of the marginal distribution of the actual home deductibles and the marginal distribution of the model-generated home deductibles.

[18] Barseghyan et al., *supra* note 12, at 612 fig. 3.

[19] *See* Levon Barseghyan et al., *The Nature of Risk Preferences: Evidence from Insurance Choices*, 103 AM. ECON. REV. 2499 (2013); Levon Barseghyan et al., *Distinguishing Probability Weighting from Risk Misperceptions in Field Data*, 103 AM. ECON. REV. PAPERS & PROC. 580 (2013).

risk preferences, a fact that motivates another important study that uses multiple domain data to investigate the nature of people's risk preferences.

B. How General Are Risk Preferences? Choices under Uncertainty in Different Domains

In an article published in the *American Economic Review* in 2012, Liran Einav et al. analyze whether and to what extent people's employee benefits choices exhibit systematic patterns, as would be implied by a domain-general component of risk preferences.[20] More specifically, the authors examine the benefits choices of 12,752 Alcoa employees in six domains: health insurance, drug insurance, dental insurance, short-term disability insurance, long-term disability insurance, and 401(k) investments. Using these data, they investigate the stability in ranking across domains of an employee's willingness to bear risk relative to his or her peers. In contrast to Barseghyan et al., who focus on testing the hypothesis of stable risk preferences, Einav et al. focus on testing the hypothesis of instable risk preferences and on quantifying the empirical importance of any domain-general component of risk preferences.

Einav et al. take two complementary approaches in their analysis. First, they take a model-free approach in which they rank by risk the options within each domain and compute the pairwise rank correlations in the employees' choices across domains. Table 1 reports their results. They find that an employee's choice in every domain is positively correlated to some extent with his or her choice in every other domain. Thus, they conclude that they can reject the null hypothesis of zero correlation, and hence the null hypothesis of no domain-general component of risk preferences.

[20] Liran Einav et al., *How General Are Risk Preferences? Choices under Uncertainty in Different Domains*, 102 AM. ECON. REV. 2606 (2012).

Table 1: Spearman Rank Correlations[21]

	Health	Drug	Dental	STD	LTD
Drug	0.400				
Dental	0.242	0.275			
STD	0.226	0.210	0.179		
LTD	0.180	0.199	0.173	0.593	
401(k)	0.057	0.061	0.036	0.029	0.028

Note: All correlations are statistically different from zero at the 1 percent level.

Second, Einav et al. take a model-based approach that is conceptually similar to the test proposed by Barseghyan et al. They first specify a model of coverage choice that assumes that employees are expected utility maximizers and that an employee's utility function has one free parameter which confounds the degree of risk aversion and other domain-specific effects (e.g., beliefs). The parameter is allowed to vary across domains (but not across employees within a given domain). Given this model—and a specific parametric utility function such as constant relative risk aversion (CRRA) or constant absolute risk aversion (CARA)—each coverage choice of an employee identifies an interval that must contain its utility parameter. Because an employee makes coverage choices in six domains, its choices imply six intervals. If the intervals overlap, then the employee's choices can be rationalized by a single coefficient of risk aversion, subject to other domain-specific effects (that do not vary across employees). In other words, if the intervals overlap, then the employee's choices reflect a stable ranking (relative to his or her peers) of risk aversion across domains.[22] The authors then search for the set of utility parameters (one for each domain) that maximize the fraction of employees whose intervals overlap. They find that this maximum fraction is 30 percent.

[21] *Id.* at 2620 tbl. 3A. Einav et al. also compute analogous correlations after controlling for potentially important covariates. The results are very similar to those reported in Table 1. *See id.* at 2620-2621 tbls. 3A & 3B.

[22] Contrast this with the Barseghyan et al. test. Under that test, if a household's intervals intersect, then the household's choices reflect a stable level (in absolute terms) of risk aversion across domains.

In summary, on the one hand Einav et al. find evidence that people's risky choices are rank correlated across contexts, leading them to reject the null hypothesis of instable risk preferences and to conclude that risk preferences have an important domain-general component. On the other hand, like Barseghyan et al., they also find evidence that most people do not exhibit stable risk preferences under the assumption of expected utility maximization, suggesting that while people's risk preferences may have a domain-general component, they may not be well represented by the expected utility model.

III. One Study on Risk Type

The two papers surveyed in the previous section exemplify how researchers can utilize multiple domain data to test and quantify the stability or instability of people's risk preferences across contexts. If risk preference is one side the human coin, then the flip side of the coin is risk type. In a similar way, therefore, researchers can use multiple domain data to explore whether and to what extent people's risk types are context-specific versus domain-general.

A case in point is an unpublished working paper by Levon Barseghyan et al.[23] In their paper, the authors use data on claims in three lines of insurance coverage—auto collision, auto comprehensive, and home all perils—to investigate the extent to which a person's claims experience in one line of coverage provides a valuable signal about his or her claim risk in other lines of coverage. The data comprise an unbalanced panel of 62,425 households who held all three coverages in one or more years between 1998 and 2006. In all, the authors' sample contains 294,917 household-year records.

Barseghyan et al. model households' claim counts using a Poisson mixture model with correlated random effects. That is, the authors assume that (i) the number of claims experienced by a household under each line of coverage follows a Poisson distribution with a coverage-specific mean and

[23] Levon Barseghyan et al., *Unlucky or Risky? Unobserved Heterogeneity and Experience Rating in Insurance Markets*, Georgetown Law and Economics Research Paper No. 12-040 (Nov. 14, 2012). Available at http://ssrn.com/abstract=2176295.

(ii) the coverage-specific Poisson means are (possibly) correlated random variables. Adopting a semiparametric, moments-based approach to estimation, they jointly estimate the regression parameters (i.e., the coefficients on observed characteristics), which determine the expected Poisson means, and the variance-covariance matrix of the random effects. From the variance-covariance estimates, they derive estimates of the cross-coverage correlations of the random effects—see Table 2. The estimates indicate, inter alia, that the random effects are positively and significantly correlated across coverages. Because the random effects capture unobserved heterogeneity in claim risk, the authors take the estimates to suggest that there is a domain-general component of risk type.

Table 2: Variance-Covariance Estimates and Implied Correlations[24]

	Estimate
Variances:	
Auto collision	0.107
Auto comprehensive	0.399
Home all perils	0.405
Covariances:	
Auto collision and auto comprehensive	0.137
Auto collision and home all perils	0.061
Auto comprehensive and home all perils	0.225
Correlations:	
Auto collision and auto comprehensive	0.663
Auto collision and home all perils	0.293
Auto comprehensive and home all perils	0.559

Note: All estimates are statistically different from zero at the 5 percent level.

After estimating the model, Barseghyan et al. attempt to demonstrate the value of the information contained in the variance-covariance estimates—and, by implication, of the signals provided by the households' claims histories about their (latent) risk types—by calculating the effect on the households' expected claim counts (i.e., their expected Poisson means) of conditioning on their

[24] Barseghyan et al., *supra* note 23, at 29 tbl. 2.

claims experience. The authors first calculate the aggregate effects when the expected claim counts are conditioned on the households' claims experience both within and across lines of coverage. Intuitively, these aggregate effects measure the combined importance of any context-specific and domain-general components of (the unobserved component of) of risk type. In an effort to measure the separate importance of any domain-general component, the authors then calculate the incremental effects of conditioning across lines of coverage (after first conditioning within lines of coverage). Table 3 summarizes the aggregate and incremental effects, all of which the authors assert are material.

Table 3: Effects on Expected Claim Counts of Conditioning on Claims Experience[25]

	Average downward revision	Average upward revision
Aggregate effect of conditioning within and across coverages:		
Auto collision	-6.6%	+10.1%
Auto comprehensive	-13.2%	+23.1%
Home all perils	-14.2%	+28.0%
	Average downward increment	Average upward increment
Incremental effect of conditioning across coverages:		
Auto collision	-3.4%	+6.9%
Auto comprehensive	-9.8%	+15.7%
Home all perils	-4.4%	+9.3%

In the remainder of the paper, Barseghyan et al. explore how households' demand for insurance would respond to experience rating—i.e., adjusting premiums to reflect the revised expected claim counts after conditioning on claims experience—under two models of risky choice: the standard expected utility model and a generalization of the standard model that features probability distortions.

[25] Barseghyan et al., *supra* note 23, at 9-10 & 31-32 tbls 4 & 5.

Calibrating the models using estimates reported elsewhere,[26] they find that (i) under the expected utility model, nearly 7 percent of households would choose a different home deductible if their premiums were experience rated, but that (ii) under the probability distortion model, only 1 percent of households would choose a different home deductible if their premiums were experience rated. The authors then proceed to discuss the normative implications of their findings for policy debates about legal restrictions on experience rating. In a nutshell, they argue that although their findings support the principal criticism of legal restrictions on experience rating—namely, that such restrictions induce "regulatory" adverse selection[27]—they also suggest that the size of the problem is likely small, in light of prior work that casts doubt on the descriptive validity of expected utility theory, and in particular the hypothesis that risk aversion is driven solely by diminishing marginal utility for wealth,[28] and of related work that points to the importance of other theories and sources of risk aversion, such as probability distortions.[29]

In their concluding remarks, Barseghyan et al. note the connection between their study on risk type and the two studies on risk preference discussed in the previous section. In particular, they remark that their study—which suggests that there is a domain-general component to risk type—complements the two prior studies, which together suggest that risk preferences, though not completely stable across contexts, also have a domain-general component.

[26] *See* Levon Barseghyan et al., *The Nature of Risk Preferences: Evidence from Insurance Choices*, 103 AM. ECON. REV. 2499 (2013).

[27] The term "regulatory" adverse selection refers to adverse selection arising from asymmetric information that is created artificially by legal restrictions on risk classification. *See* Michael Hoy, *Categorizing Risks in the Insurance Industry*, 97 Q. J. ECON. 321 (1982).

[28] *See, e.g.*, Sydnor, *supra* note 1; Barseghyan et al., *supra* note 12.

[29] *See, e.g.*, Barseghyan et al., *supra* note 26.

IV. Preliminary Conclusions

Multiple domain data equals big data. In the social sciences, moving from single domain data to multiple domain data enables researchers to paint a more complete picture of human nature.[30] A perfect example is the literature on risk preference and risk type. The three studies surveyed in this chapter—two on risk preference and one on risk type—demonstrate how social scientists can leverage multiple domain data to gain a deeper understanding of the nature of people's tolerance for bearing risk and their propensity to generate risk. In particular, these studies provide evidence that neither risk preference nor risk type is entirely context-specific—both have important domain-general components. Such conclusions could not be reached using single domain data. Indeed, with single domain data one could not hope to investigate the extent to which people's risk preferences or risk types are context-specific versus domain-general. Multiple domain data is required for such inquiries.

The promise of multiple domain research, however, reaches beyond the ability to test the hypothesis that a given aspect of human nature is stable across contexts. For example, we can use multiple domain data to sharpen the inferences we make about human nature from people's behavior. For instance, if we treat stability across contexts not as a testable hypothesis but rather as a model selection criterion, we can use multiple domain data as a filter for choosing the best model of human behavior—the best model is the one that best explains people's behavior across the multiple domains.[31]

Having a better understanding of human behavior is key to making better law and public policy. After all, every normative claim about what constitutes the optimal legal rule or government policy rests on assumptions, sometimes explicit but often implicit, about human behavior and human nature.

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[30] Of course, researchers sometimes face unique challenges in attempting to compile multiple domain data. A frequent challenge is developing a protocol to match data on human subjects from different sources that complies with the privacy and confidentiality requirements imposed by federal law and institutional review boards.

[31] *See, e.g.*, Levon Barseghyan et al., *Inference under Stability of Risk Preferences* (Apr. 3, 2013) (presented at the 2013 Spring Meeting of the NBER Insurance Working Group).

Consider, for example, the fundamental question of which basic tort liability rule—negligence or strict liability—is socially optimal in the sense of minimizing the social costs of accidents. The standard models that legal economists use in their analyses of this question are based on the expected utility framework. However, a considerable body of research—including, notably, the multiple domain research on risk preference discussed in this chapter—suggests that the expected utility framework is incorrect or at least incomplete. This is turn suggests that the conventional wisdom of the economic analysis of tort law may be incorrect or incomplete. For instance, in cases where the injurer's level of care is the only determinant of accident risk, a standard result in the literature is that negligence and strict liability are both efficient—the injurer will take optimal care under either rule.[32] However, in an article published in the *Journal of Legal Studies* in 2007, I show that if injurers face ambiguity about accident risk—a possibility that the expected utility model cannot accommodate, but that a probability distortion model can—the standard result does not hold, and instead negligence is generally superior to strict liability.[33]

The era of multiple domain data is here. To answer many of the big questions in social science, all of which have important lessons for those of us interested in evidence-based law and public policy, more multiple domain data—and more research using multiple domain data—is needed.

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[32] *See, e.g.*, STEVEN SHAVELL, ECONOMIC ANALYSIS OF ACCIDENT LAW (1987). This result assumes that the parties either are risk neutral or purchase full coverage against accident risk in a perfectly competitive insurance market.

[33] *See* Joshua C. Teitelbaum, *A Unilateral Accident Model under Ambiguity*, 36 J. LEGAL STUD. 431 (2007). A person faces ambiguity about a risk if the person's beliefs about the risk cannot be represented by a probability measure. Ambiguity is also known as Knightian uncertainty, in recognition of the distinction famously made by the economist Frank Knight between "risk" (measurable uncertainty) and "uncertainty" (unmeasurable uncertainty). *See* FRANK H. KNIGHT, RISK, UNCERTAINTY, AND PROFIT 19-21 (1921).