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Consumers incorrectly rely on their sense of understanding of what a company does to evaluate investment risk. In three correlational studies, greater sense of understanding was associated with lower risk ratings (Study 1) and with prediction distributions of future stock performance that had lower standard deviations and higher means (Studies 2 and 3). In all studies, sense of understanding was unassociated with objective risk measures. Risk perceptions increased when the authors degraded sense of understanding by presenting company information in an unstructured versus structured format (Study 4). Sense of understanding also influenced downstream investment decisions. In a portfolio construction task, both novices and seasoned investors allocated more money to hard-to-understand companies for a risk-tolerant client relative to a risk-averse one (Study 5). Study 3 ruled out an alternative explanation based on familiarity. The results may explain both the enduring popularity and common misinterpretation of the “invest in what you know” philosophy.

Keywords: sense of understanding, risk perception, financial decision making, heuristics and biases

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Circle of Incompetence: Sense of Understanding as an Improper Guide to Investment Risk

> I have an old-fashioned belief that I can only expect to make money in things that I understand. And when I say “understand,” I don’t mean understand what the product does.... I mean understand what the economics of the business are likely to look like ten years from now.... Evaluating that company is within what I call my circle of competence.
>
> —Warren Buffett, speech at University of Georgia, 2001

Consumers increasingly utilize the stock market to save money and increase wealth. In the United States, 14% of households invest in individual company stock, averaging $294,000 per household (median: $27,000; Federal Reserve Bank 2014). In China, an estimated 200 million consumers invest in individual company stock, constituting 85% of all stock trades in the country (Shen and Goh 2015). Worldwide, consumers risk a substantial amount of money with decisions regarding the companies in which they invest. Thus, an important question is: How should consumers select investments?

Warren Buffett once said that investors should “draw a circle around the companies you understand” when beginning to select investments (*Forbes* 1974). The advice to “invest in what you know” has become a common refrain from financial

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experts and personal finance gurus (Buffett 1992; Cramer 2013; Lynch 1989). The logic behind this strategy is that it exploits the investor's local knowledge (Hayek 1945). When an investor possesses expertise, (s)he is in a better position to identify an undervalued company or asset. Obviously, understanding what a company does is merely a starting point to evaluating the investment opportunity.

Unfortunately, people often misunderstand and misapply this advice, confusing a vague sense of understanding with the deep fundamental research that Buffett and others are talking about. Peter Lynch, one of the investors most closely associated with the "invest in what you know" strategy, lamented that, "I've never said, if you go to a mall, see a Starbucks and say it's good coffee, you should call Fidelity brokerage and buy the stock.... People buy a stock and they know nothing about it (Schoenberger 2015)." Investment companies sometimes play into people's misunderstanding, encouraging investment based on shallow research. In 2015, Fidelity released a mobile app called "Stocks Nearby," which, according to their press materials, "enables investors to immediately research businesses that show promise—on the go. Imagine an investor coming upon a store that is packed with customers—with Stocks Nearby they can easily begin to answer the question if it's a good investing opportunity" (Fidelity 2015).

In this article, we argue that people rely on their sense of understanding of what a company does as an indicator of investment risk. Easy-to-understand companies are construed as safe investments, whereas hard-to-understand companies are viewed as risky. This explains why people find the "invest in what you know" philosophy so compelling. Unfortunately, perceived understanding of what a company does is a poor guide to actual investment risk, which may explain why lay investors often misapply the philosophy. Because perceived understanding is a poor predictor of actual risk, relying on it will lead investors to take on more or less risk than they intend.

SENSE OF UNDERSTANDING

There is a growing body of evidence that people's sense of understanding is a major driver of their attitudes, preferences, and choices. Consumers prefer novel products they feel they understand (Fernbach, Sloman, et al. 2013; Jhang, Grant, and Campbell 2012). Consumers are more willing to enroll in retirement investment accounts and invest in risky assets when they feel more knowledgeable about the general field of investing (Hadar, Sood, and Fox 2013; He, Inman, and Mittal 2008; Krueger and Dickson 1994). In addition, they trade stocks more often when they feel more comfortable with their ability to understand investment products and opportunities (Graham, Harvey, and Huang 2009).

Sense of understanding is an important cue for decision making because it reflects processes of explanation that form the basis of how people make sense of the world. The sine qua non of human cognition is the ability to develop a base of knowledge that allows us to deal with uncertainty and choose effective actions in new situations (Craik 1967). The importance of these processes is apparent from the fact that young children doggedly pursue explanations and differentiate truly explanatory responses from tautological ones (Frazier, Gelman, and Wellman 2009, 2016). The understanding process is often punctuated by a subjective feeling of insight, indicating that one has a sufficiently accurate explanation (Trout 2002). Gopnik (1998) compares this moment to a sexual orgasm in that its pleasure may be an evolutionary adaptation to encourage people to seek out causal understanding. This feeling can be illusory (Fischhoff, Slovic, and Lichtenstein 1977; Mazumdar and Monroe 1992; Schacter 1983), but it correlates with true understanding in that it occurs after a problem has been analyzed to some extent. Thus, it makes sense that people rely on their sense of understanding to guide decision making.

SENSE OF UNDERSTANDING AND RISK

Two Dimensions of Risk

Our key hypothesis is that sense of understanding affects decision making by influencing risk assessments. A key function of understanding is to support predictive inference. Understanding entails constructing a mental model of a system that reflects the causal relations among its parts, and the model can be used to assess the probability of outcomes under different counterfactuals (Fernbach, Darlow, and Sloman, 2011; Glymour 2001; Gopnik et al. 2004; Rottman and Hastie 2014; Sloman 2005). These probabilities underlie what decision theorists call "risk assessments." Therefore, there is a deep connection between the psychology of understanding and the psychology of risk.

Unpacking this connection requires defining risk perception more precisely. Broadly, there are two traditions of research on risk perception in the behavioral sciences (Fox, Erner, and Walters 2016). The first tradition, exemplified by Slovic's (1987) "psychometric" approach, attempts to identify the qualitative characteristics of events that make them feel risky. Researchers in decision theory and finance have instead sought to define risk and risk perception in terms of objective properties of probability distributions. For instance, investment risk is often defined as the mean and variance of the outcome distribution of the asset under consideration (Arrow 1965; Markowitz 1952; Pratt 1964). Although these traditions differ in their approaches, they both offer coherent and complementary insights.

In the qualitative tradition, Slovic (1987; see also Fischhoff et al. 1978) identified two dimensions that drive people's risk perceptions, which he termed "unknown risk" and "dread risk." Unknown risk is characterized by hazards that are unknowable, unobservable, and new, reflecting a sense of uncertainty. Dread risk is characterized by hazards with large, negative consequences and a high probability of loss, reflecting a focus on negative outcomes. More colloquially, unknown risk reflects the concern that "anything might happen," whereas dread risk reflects the concern that "something bad might happen." These two dimensions explain risk taking across a broad range of contexts including societal risks (e.g., nuclear power), public safety (e.g., car accidents), and personal health (e.g., smoking; Fischhoff et al. 1978; Johnson and Tversky 1983, 1984; Lindell and Earle 1983).

A parallel idea has emerged in the decision-theory tradition, in which risk perception has been related to both the variance and the mean of the distribution of possible outcomes (March and Shapira 1987; Weber, Shafir, and Blais 2004). Decision options feel risky both when the variance of possible outcomes is high—analogous to unknown risk—and when there is a higher probability of negative outcomes and a lower probability of positive outcomes, indicating that the mean of possible outcomes is low—analogous to dread risk.

Hypothesized Relationships

A key contribution of this article is to measure perceived risk using rich elicitation methods that enable us to disentangle effects of sense of understanding on the two dimensions of risk. For this purpose, we ask participants in Studies 2 and 3 to generate distributions of expected stock prices using a "distribution builder" tool, and we examine how sense of understanding relates to the variance and the mean of those distributions. In Study 4, we develop a bidimensional risk perception scale.

We hypothesize that sense of understanding influences both components of risk. Learning about a company involves constructing a mental model explaining how the company works. If people are confident that their mental model is accurate, they should believe they are in a better position to make precise predictions about a company's performance, reducing the variance of expected future stock prices. Consistent with this notion, sense of understanding is associated with expressing greater certainty about one's attitudes (Fernbach, Rogers, et al. 2013), and those that think about gaps in their knowledge tend to be less overconfident (Walters et al. 2016).

There are also reasons to believe that sense of understanding should be related to the mean of expected outcomes. The information integration literature suggests that people evaluate an alternative less favorably if they lack information about the alternative along multiple dimensions (Jaccard and Wood 1988; Johnson and Levin 1985). People may also infer that easy-to-understand companies perform better on other dimensions. For instance, people may believe that the management of companies they understand is better, or that those companies have fewer liabilities. Finally, the sense of understanding has a hedonic component—explaining a phenomenon generates positive affect (Gopnik 1998). This could lead people to make more favorable predictions about a company's performance and stock price.

The relationship between sense of understanding and the mean of expected outcomes need not necessarily be positive. Clear descriptions of what a company does could illuminate flaws in a business model that remain hidden in more ambiguous descriptions. Thus, one might observe that people predict less favorable outcomes for companies that are rated as easier to understand. However, the literature has shown that, in general, people prefer things they understand, suggesting that usually the relationship is positive (Campbell and Goodstein 2001; Fernbach, Sloman, et al. 2013; Hadar, Sood, and Fox 2013; Jhang, Grant, and Campbell 2012; Peter and Ryan 1976).

The research most closely related to the present investigation is the work of Hadar, Sood, and Fox (2013), who showed that consumers preferred financial products when they felt knowledgeable about them, holding constant objective knowledge. The authors did not measure risk perceptions, but it is possible that perceived risk mediates their effects. One benefit of analyzing preferences through the lens of risk perception is that it allows more nuanced predictions about the relationship between subjective knowledge and preference. In Study 5, we show that greater understanding does not always lead to greater preference. Investors who desire more risk allocate more money to poorly understood companies than well-understood ones.

Ecological Validity

Having derived our key hypothesis that sense of understanding serves as a cue to investment risk, we next consider whether it is likely to be a good or bad cue. For sense of understanding to be a good cue to risk, two conditions must be met: (1) true understanding must actually predict risk and (2) people must be able to accurately assess their understanding. The first criterion often holds. Consider new product adoption: if one truly understands the mechanisms by which a novel product delivers a benefit, it should increase one's belief that the benefit will actually be obtained, and it makes sense to be wary of products one does not understand. However, the second criterion is often violated because people are bad at evaluating how well they understand things (Alba and Hutchinson 2000; Carlson et al. 2009), and many consumers have low thresholds for what they deem to be satisfactory understanding (Fernbach, Sloman, et al. 2013). The more knowledgeable people feel in a given domain, the more determined they are to rely on their personal judgment (Heath and Tversky 1991). However, their personal judgment is more accurate with more objective (vs. subjective) knowledge. Lack of calibration between subjective and objective understanding is a major problem in financial decision making. Hadar, Sood, and Fox (2013) showed that consumers were more likely to invest in an asset when subjective knowledge was higher, controlling for objective knowledge. Increasing objective knowledge did not affect preferences, suggesting that subjective knowledge is often a more important driver of financial decisions than objective knowledge. Consistent with this notion, Fernandes, Lynch, and Netemeyer (2014) found that consumers' confidence in recognizing good investments explains more variability in downstream financial behaviors than their financial literacy.

What about the investment context we explore in this article? A sense of understanding of what a company does would seem to be a poor cue for objective risk because both the aforementioned criteria are likely to be violated. People are likely to confuse a shallow understanding of a company's operations with the complex reality of most businesses. It is easy to understand that Starbucks sells coffee, but truly understanding the business requires much more, including knowledge of product lines, distribution channels, supply chains, real estate, and so on. Even if one truly understands a business's operations, this knowledge is unlikely to provide much insight into investment risk, which depends on a complex network of interacting forces, such as competition between firms (Grossman and Shiller 1980), new entrants to the industry, the bargaining power of suppliers and consumers (Porter 1979, 2008), and the customer equity of the firm (Aksoy et al. 2008; Anderson, Fornell, and Mazvancheryl 2004; Kumar and Shah 2009). Clearly, this goes far beyond an assessment of what the company does. We test the ecological validity of reliance on sense of understanding by collecting objective risk data used in our studies.

RELATED CONSTRUCTS

Familiarity is a highly studied construct that has been related to preference and risk in previous research. It is usually defined in terms of recognition (Goldstein and Gigerenzer 2002), and it increases with prior exposure (Alba and Hutchinson 1987; Zajonc 2001). Colloquially, the word "familiarity" can be used more broadly, in a way that essentially means the same thing as "sense of understanding" (e.g., "I am familiar with the company's operations"). Following the literature, we define familiarity in the narrower sense. Familiar companies are those that one recognizes on the basis of actual or perceived prior exposure.

Many studies have shown that familiarity promotes positive affect, leading people to like objects more (e.g., Alter and Oppenheimer 2008; Zajonc 2001). Within the financial domain, researchers have found that more familiar companies are more popular investments (Grullon, Kanatas, and Weston 2004) and contain a larger proportion of consumer investors (Frieder and Subrahmanyam 2005). Familiarity is often studied along with fluency, the ease with which a stimulus is processed (Clore 1992; Jacoby, Kelley, and Dywan 1989; Whittlesea, Jacoby, and Girard 1990). There is a bidirectional relationship between fluency and familiarity, such that stimuli that are processed more fluently seem more familiar, and more familiar stimuli are processed more fluently (Koriat and Levy-Sadot 2001; Whittlesea, Jacoby, and Girard 1990). One article has shown that fluency can increase perceived risk by increasing the feeling of familiarity. Song and Schwarz (2009) showed that hard-to-pronounce products were viewed as unfamiliar, which in turn resulted in heightened risk perceptions. For instance, a food additive called "Magnalroxate" was rated as more familiar and less risky than one called "Hnegripitrom."

Familiarity with a company is conceptually distinct from the sense of understanding of what the company does. Consider an American reading a description of a supermarket chain from Russia. This person's subjective understanding of what the company does would likely be high, and familiarity with the company low. To differentiate our results empirically from previously documented effects of familiarity on preference and risk, we show effects of perceived understanding on risk controlling for familiarity (Studies 1 and 2) and when we manipulate understanding but leave the information content about companies constant, thus equating familiarity across conditions (Study 4). Even stronger evidence comes from Study 3, which we designed specifically to address this issue. In this study, information content was the same across conditions, and we just varied the name of the company to be well known versus unknown. The results of these studies provide strong evidence against a familiarity account of our findings.

Another concept that we want to distinguish from sense of understanding is the aleatory versus epistemic nature of an uncertain outcome (Fox and Ülkümen 2011; Knight 1921). Aleatory uncertainty is characterized by inherent stochasticity (e.g., the roll of a die), whereas epistemic uncertainty is characterized by insufficient knowledge (e.g., whether a store has a certain product in stock). The aleatory versus epistemic nature of uncertainty is also conceptually distinct from the sense of understanding of what a company does. A person may view the performance of Starbucks as influenced primarily by aleatory factors (e.g., how weather events affect coffee crop production) or epistemic factors (e.g., how well trained the staff is), regardless of how well they feel they understand what Starbucks does. Ülkümen et al. (2014) showed that people reported larger confidence intervals around stock prediction forecasts when they perceive the company's revenue as more aleatory in nature. In contrast, epistemic uncertainty was unrelated to confidence interval width. In Studies 1 and 2, we examine the relationship between understanding and risk, controlling for differences in aleatory and epistemic uncertainty.

STUDY 1: SENSE OF UNDERSTANDING AND RISK RATINGS

The goal of Studies 1 and 2 was to provide correlational evidence that people rely on their sense of understanding to judge investment risk, despite understanding being unrelated to the objective risk of a company's stock. To show the breadth of this phenomenon, we collected measurements of understanding and risk for all S&P 500 companies. In Study 1, we measured perceived risk using a simple rating scale. In Study 2, participants made performance forecasts, and we inferred perceived risk by analyzing the central tendency and dispersion of the forecasts. To measure objective risk, we computed the rate of return and the volatility of each stock using historical data. We predict that sense of understanding will significantly correlate with perceived risk but not objective risk.

In addition, we measured perceived familiarity, liking, reputation, and the epistemic and aleatory risk scale (EARS; Fox, Erner, and Walters 2018). Sense of understanding is related to, but conceptually distinct from, these constructs. We expect to find a relationship between sense of understanding and perceived risk after controlling for these variables.

Method

Respondents from Amazon Mechanical Turk (MTurk) completed Study 1 for payment. Participants rated ten companies randomly selected from the S&P 500. For each company, participants first read a company profile downloaded from Yahoo Finance, providing a short overview of the company, followed by a more detailed explanation of the different divisions of the company. For an example of a company profile, see Web Appendix A.

When study materials were collected, Yahoo Finance did not contain profiles for 19 S&P 500 companies. In addition, one company completed a merger shortly before data collection, preventing us from calculating objective performance statistics. Thus, the study included 480 companies. For each company, we calculated the rate of return and capital asset pricing model (CAPM) beta using monthly stock price data over a one-year time horizon after data collection. Rate of return is the percent change in the value of the stock, including dividends and other distributions. Higher values indicate a smaller expected probability and severity of losses, and therefore less risk. The CAPM beta is the expected ratio of a stock's return to the overall market's return. A company with a beta of 2 tends to have double the rate of return of the market, doubling both gains and losses. Higher values indicate more uncertainty about the rate of return and, therefore, more financial risk. For a detailed explanation of how we computed rate of return and CAPM beta, see Web Appendix B.

After reading each company profile, participants completed a set of measures described in Table 1. Participant ratings were collected in two samples. In the first sample ($N = 248$), participants rated perceived risk, sense of understanding, familiarity, and the EARS scale, in that order.[1] We later measured

[1]The EARS scale currently exists in ten- and four-item versions. We used an earlier six-item version. All six items are included in the current ten-item version, and four of the six items make up the current four-item version.

Table 1
SUMMARY STATISTICS AND CORRELATIONS FOR STUDY 1

	M	*SD*	*α*
1. Perceived risk	3.63	.86	
How risky would you rate [company]'s stock? (1 = "Not at all risky," and 7 = "Extremely risky")			
2. Sense of Understanding	5.41	.85	
How well do you understand what [company] does? (1 = "I do not understand at all," and 7 = "I understand completely")			
3. Familiarity	2.93	1.71	
How familiar were you with [company] before reading the profile? (1 = "Not at all," and 7 = "A lot")			
4. Liking	4.48	.65	
How much do you like [company]? (1 = "Strongly dislike," and 7 = "Strongly like")			
5. Reputation	4.49	.92	
Prior to reading the description, what did you think of the reputation of [company]? (1 = "Very negative reputation," 7 = "Very positive reputation," and 8 = "N.A.")			
6. Epistemic uncertainty	3.63	.38	.81
The yearly earnings of [company] ... (1 = "Strongly disagree," and 5 = "Strongly agree")			
... is knowable in advance, given enough information.	3.47	.49	
... is something that becomes more predictable with additional knowledge or skills.	3.78	.42	
... is something that well-informed people would agree on.	3.64	.45	
7. Aleatory uncertainty	3.16	.50	.86
The yearly earnings of [company] ... (1 = "Strongly disagree," and 5 = "Strongly agree")			
... is determined by chance factors.	3.03	.57	
... could play on in different ways on similar occasions.	3.36	.49	
... is something that has an element of randomness.	3.09	.62	
8. Rate of return	.07	.24	
9. CAPM beta	1.05	.70	

	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Perceived risk								
2. Sense of understanding	−.30*							
3. Familiarity	−.24*	.51*						
4. Liking	−.26*	.22*	.34*					
5. Reputation	−.22*	.18*	.23*	.73*				
6. Epistemic uncertainty	−.48*	.39*	.23*	.14*	.17*			
7. Aleatory uncertainty	.55*	−.14*	−.11*	−.15*	−.13*	−.44*		
8. Rate of return	−.07	.06	.19*	.24*	.17*	.05	−.11*	
9. CAPM beta	.03	−.04	−.03	.07	.05	.02	.04	−.17*

*$p < .05$.
Notes: Statistics were calculated after data aggregation and, thus, N = 480.

liking and reputation in a second sample (N = 574), following the same procedure. Following prior literature (e.g., Song and Schwarz 2009; Thorndyke 1977), we used single-item scales for all measures in this study, except the EARS scale. In subsequent studies, we measure perceived risk and sense of understanding with multi-item scales.

Results and Discussion

We analyzed the data at the company level, averaging ratings for each company across all participants who rated it. A median of 5 participants from the first sample and 11 from the second sample rated each company. As with all studies in this article, we tried to limit data exclusions as much as possible and excluded data only when necessary to estimate the statistical models. In this study, we removed 78 ratings across 53 participants who failed to complete all measures on one or more of the ten companies presented to them. In addition, the reputation question had a not applicable (N.A.) option, and ten companies were excluded from the analysis because they only received N.A. ratings for reputation. Our analysis is, thus, based on average ratings for 470 companies from the S&P 500. When we exclude reputation and include all 480 companies, the results for our focal variables, sense of understanding and risk perception, remain the same.

Table 1 shows the correlations between measurements in Study 1. As we predicted, a greater sense of understanding was associated with lower perceived risk ($r = -.30$, $p < .001$) but was not associated with either rate of return ($r = .06$, $p > .16$) or CAPM beta ($r = -.04$, $p > .40$). We conducted regression analyses to assess the relationship between understanding and perceived risk controlling for other variables. As we predicted, the relationship between sense of understanding and perceived risk remained significant with all controls included ($t(461) = -2.28$, $p < .03$). Furthermore, there was no significant relationship between perceived risk and rate of return ($t(461) = 1.07$, $p > .29$) or CAPM beta ($t(461) = .81$, $p > .42$). We present the regression results in Table 2, along with similar regressions from Studies 2 and 3.

In summary, Study 1 revealed that as people felt they better understood what a company does, they also felt investing in that company was less risky. However, better understanding was not related to either measure of objective risk. Study 1 also conceptually replicated prior findings. Song and Schwarz (2009) found that objects whose names are easier to pronounce are judged as less risky because they seem more familiar.

Table 2
REGRESSION RESULTS FOR STUDIES 1–3

	Study 1	*Study 2*									*Study 3*	
		Dispersion				*Central Tendency*			*Hybrid*			
	Risk	*SD*	*Var*	*IQR*	*MAD*	*M*	*Med*	*P(loss)*	*CV*	*Relative M*	*SD*	*M*
Understanding	−.10* (.04) [.01]	−.20* (.05) [.03]	−1.4* (.42) [.03]	−.29* (.10) [.02]	−.10 (.07) [.00]	.31* (.09) [.03]	.28* (.10) [.02]	−.03* (.01) [.04]	−.03* (.01) [.03]	.20* (.04) [.05]	−.10* (.03) [.02]	.23* (.08) [.01]
Familiarity	−.03 (.02) [.00]	.10* (.03) [.02]	.69* (.26) [.02]	.17* (.06) [.02]	.06 (.04) [.00]	−.05 (.05) [.00]	−.05 (.06) [.00]	.01* (.004) [.01]	.01* (.004) [.02]	−.05 (.03) [.01]	−.10 (.12) [.00]	.36* (.16) [.01]
Liking	−.13 (.07) [.01]	−.19 (.12) [.01]	−1.4 (.90) [.01]	−.44* (.20) [.01]	−.22 (.15) [.00]	.32 (.19) [.01]	.39 (.22) [.01]	−.03* (.02) [.01]	−.04* (.01) [.01]	.13 (.09) [.00]		
Reputation	−.03 (.05) [.00]	.03 (.08) [.00]	.12 (.62) [.00]	.12 (.14) [.00]	.05 (.10) [.00]	.11 (.13) [.00]	.11 (.15) [.00]	−.01 (.01) [.00]	.00 (.01) [.00]	.02 (.06) [.00]		
Epistemic uncertainty	−.49* (.10) [.04]	−.21 (.12) [.01]	−1.9* (.91) [.01]	−.37 (.21) [.01]	−.23 (.15) [.01]	.49* (.19) [.01]	.52* (.22) [.01]	−.04* (.02) [.02]	−.04* (.02) [.01]	.19* (.09) [.01]		
Aleatory uncertainty	.71* (.07) [.18]	.26* (.10) [.02]	2.3* (.76) [.02]	.35* (.17) [.01]	.35* (.13) [.02]	−.62* (.16) [.03]	−.66* (.18) [.03]	.03* (.01) [.01]	.04* (.01) [.02]	−.31* (.08) [.03]		
Rate of return	.15 (.14) [.00]	.12 (.21) [.00]	1.0 (1.6) [.00]	.30 (.38) [.00]	.07 (.27) [.00]	−.08 (.34) [.00]	−.13 (.40) [.00]	.00 (.03) [.00]	.02 (.03) [.00]	−.00 (.17) [.00]		
CAPM beta	.04 (.04) [.00]	−.08 (.07) [.00]	−.68 (.55) [.00]	−.05 (.13) [.00]	−.10 (.09) [.00]	.01 (.11) [.00]	.03 (.13) [.00]	−.00 (.01) [.00]	−.01 (.01) [.00]	−.01 (.06) [.00]		
Under. × Fam.											−.03 (.03) [.00]	−.09 (.08) [.00]
N	470	443	443	443	443	443	443	443	443	443	100	100
R^2	.41	.08	.08	.06	.04	.12	.09	.12	.12	.12	.76	.31
F	47.62	5.14	5.29	4.14	2.64	8.29	6.45	8.51	8.05	8.47	—	—
p	.000	.000	.000	.000	.01	.000	.000	.000	.000	.000	—	—

*$p < .05$.

Notes: IQR = interquartile range; MAD = median absolute deviation. Table 2 includes regression weight estimates, with standard errors in parentheses, and η^2 in brackets. For Study 3, familiarity was manipulated and was coded −1 for low familiarity and 1 for high familiarity. We used linear mixed models in Study 3; thus, omnibus F-statistics were not computable. Likelihood ratio tests between each model and its respective null model were significant (SD = $\chi^2(3) = 20.21$, $p < .001$; M = $\chi^2(3) = 15.12$, $p < .002$). We computed R^2 and η^2 statistics, for these models, using the unpenalized residual sum of squares. Models were estimated using the lme4 package in R (Bates et al. 2015), and degrees of freedom were estimated using the Kenward–Roger approximation (Kenward and Roger 1997).

Our results extend this finding to the financial domain. Ülkümen et al. (2014; Study 3) found that aleatory uncertainty was positively related to the width of confidence intervals around earnings forecasts for investments. Wider confidence intervals indicate that people are less certain of their predictions and thus suggest higher risk. Our results conceptually replicated this finding using a different risk measure. Whereas Ülkümen et al. did not find a significant relationship with epistemic uncertainty, we found a negative relationship between epistemic uncertainty and risk perceptions. One reason for this discrepancy may be that the simple rating scale we used measures dimensions of risk that are not reflected in confidence intervals. In Study 2, we found support for this explanation.

STUDY 2: DISTRIBUTION BUILDER

Study 2 was similar to Study 1 but measured perceived risk in a different way. Instead of rating perceived risk on a scale, participants made 100 predictions for a company's future stock price. Prior research has shown that this technique accurately elicits probabilistic beliefs (Goldstein and Rothschild 2014; Reinholtz, Fernbach, and De Langhe 2016). We then calculated various summary statistics of the prediction distribution as measures of risk. As we discussed previously, the subjective feeling of risk includes a component related to the uncertainty of outcomes and a component related to the likelihood and severity of negative outcomes (Slovic 1987). In Study 2, we operationalized these components as the dispersion (e.g., standard deviation) and central tendency (e.g., mean) of prediction distributions, respectively. Less dispersed distributions indicate less perceived risk because the person is more certain that particular outcomes are likely to occur and sees fewer outcomes as possibilities. Distributions with a higher central tendency indicate less perceived risk because the person expects that losses are less likely to occur relative to gains or that losses are less severe. Thus, we predicted that greater sense of understanding would be associated with lower measures of dispersion and higher measures of central tendency.

Method

Undergraduate business students (N = 335) participated in the study for course credit. Stimuli and measures were identical to Study 1, except that we measured risk perceptions with a distribution builder (for an example, see Figure 1). Participants assigned 100 balls to different uniformly spaced bins representing 11 possible rates of return after one month. Participants were instructed to assign balls to bins based on how likely they thought each rate of return was, and that they should assign the most balls to the rate of return they thought was most likely. Participants first completed a practice task on the distribution builder, specifying that the third outcome was most likely and the second outcome was least likely. After completing the practice task, participants read and rated four random profiles of S&P 500 companies. After reading each profile, participants first completed the distribution builder task and then rated understanding, familiarity, and the EARS scale. We computed new rate of return and CAPM beta statistics for each company and included the average company liking and reputation ratings used in Study 1.

Results and Discussion

We first calculated summary statistics for each prediction distribution. Since each bin was labeled with a range of values

Figure 1

DISTRIBUTION BUILDER TASK

(e.g., 7%–9%), we assigned each prediction the midpoint of that range (e.g., 8%), and assigned 10% and −10% to the highest and lowest bins. We used the standard deviation and mean as our primary measures of risk but replicated our analysis with other measures as well.[2] Conclusions based on the alternative measures are the same as for the mean and standard deviation. All results are included in Table 2, but we discuss only the results for the mean and standard deviation next.

We analyzed the data at the company level. For each company, we averaged summary statistics and scale ratings across participants who rated that company. A median of three participants rated each company. We removed 89 ratings from the data set because of incomplete data. Out of 500 possible companies in the S&P 500, 432 were used for analysis. The 68 remaining companies comprised 19 that did not have profiles on Yahoo Finance, 4 that went out of

[2]For alternative dispersion measures, we also computed the variance, interquartile range, and median absolute deviation. For alternative central tendency measures, we computed the median and the probability of a loss (p(loss); i.e., the number of predictions in the five bins with negative rates of return divided by the total number of predictions). Finally, we computed two hybrid measures that combine both the dispersion and central tendency, coefficient of variation (CV) and relative mean. Coefficient of variation is the standard deviation of a distribution divided by the mean. It has been shown to accurately measure a person's subjective assessment of risk (Weber, Shafir, and Blais 2004) and is undefined for nonratio scales because CV can become negative or infinite if the mean is negative or zero, which are both uninterpretable. As a method of transforming our data into a ratio scale, we added 10 to all predictions prior to calculating a distribution's CV, so the values ranged from 0 to 20 rather than −10 to 10. The relative mean is the mean of a distribution divided by the standard deviation and is analogous to the Sharpe Ratio, a measure of an asset's returns relative to its financial risk (Sharpe 1966).

business prior to data collection, 27 that were never randomly sampled during data collection, and 18 that contained only incomplete data.

Table 3 includes the correlations between all measures in Study 2. As we predicted, greater sense of understanding was associated with smaller prediction standard deviations, indicating more certainty about predictions ($r = -.17$, $p < .001$), as well as higher prediction means, indicating less likely and less severe losses ($r = .20$, $p < .001$). Also as we predicted, sense of understanding was not associated with CAPM beta ($r = -.01$ $p > .83$) or rate of return ($r = .02$, $p > .56$). We conducted regression analyses to assess the relationship between understanding and the two components of perceived risk, controlling for the other variables. The results are presented in Table 2, which also includes regression results for alternative measures of dispersion and central tendency.

After controlling for other variables, better-understood companies still had smaller prediction standard deviations, indicating less perceived risk ($t(423) = -3.69$, $p < .001$), but prediction standard deviations had no significant relationship with rates of return ($t(423) = .56$, $p > .57$) or CAPM beta ($t(423) = -1.15$, $p > .25$). In the second regression, after controlling for other variables, better-understood companies still had larger prediction means, also indicating less perceived risk ($t(423) = 3.50$, $p < .001$), but prediction means were not significantly related to rates of return ($t(423) = -.22$, $p > .82$) or CAPM beta ($t(423) = .09$, $p > .93$).

In summary, Studies 1 and 2 found that people believe it is less risky to invest in a company when they feel they have a better understanding of what the company does. Study 1 showed that understanding is related to ratings of perceived risk and Study 2 showed that understanding is related to risk measures derived from a stock return prediction task. Sense of understanding was related to less dispersed predictions and higher average predictions. These results held up after controlling for several potentially confounding variables. In both studies, sense of understanding and perceived risk were unrelated to objective risk. Participants were unable to evaluate the riskiness of stocks, and their sense of understanding was not a good proxy for investment risk.

STUDY 3: MANIPULATING FAMILIARITY

The purpose of Study 3 was to further disentangle our key construct of perceived understanding from familiarity. Prior research on familiarity has established that people tend to like things better when they are familiar with them (Alter and Oppenheimer 2008; Reber, Winkielman, and Schwarz 1998; Zajonc 2001), but the relationship between familiarity and risk perception is less established. Song and Schwarz (2009) found that higher familiarity led to decreased risk perceptions. However, because perceived risk was measured with a single rating, it is not clear which components of risk perception are related to familiarity.

Method

Respondents from MTurk ($N = 100$) completed Study 3 for payment. We randomly selected one company profile used in Studies 1 and 2 from 12 industry groups in the Global Industry Classification Standard, a taxonomy for classifying companies with similar production processes, products, or market behavior. We removed identifying information including the company name, subbrands, headquarters, CEO name, and founding date. To manipulate familiarity, participants received profiles where the company name was replaced with the name of either the most familiar or least familiar company within the profile's industry group (based on ratings from Studies 1 and 2). For instance, we used Gap Inc. (high familiarity) or L Brands (low familiarity) for the retailing industry. The profiles were otherwise identical.

For each profile, participants first completed the same distribution builder task as in Study 2, except we asked participants to make predictions for the change in stock price after one year rather than one month. After completing the distribution builder, participants rated understanding and familiarity on the same seven-point scales as in Studies 1 and 2. For summary statistics of the measures, see Web Appendix C.

Results and Discussion

We first assessed whether the familiarity manipulation was successful. We conducted two mixed analyses of variance (ANOVAs); one with familiarity ratings as the dependent variable and one with understanding ratings as the dependent variable. As we expected, familiarity ratings were significantly higher in the high-familiarity condition ($M_H = 5.72$, $M_L = 2.04$; $t(98) = 16.19$, $p < .001$, $d = 3.23$). In addition, the familiarity manipulation did not significantly affect understanding ratings ($M_H = 6.10$, $M_L = 5.93$; $t(98) = .86$; $p > .39$, $d = .17$).

Table 3
SUMMARY STATISTICS AND CORRELATIONS FOR STUDY 2

	M	*SD*	*α*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
1. Prediction SD	3.39	1.08										
2. Prediction mean	1.77	1.76		−.26*								
3. Understanding	4.75	1.08		−.17*	.20*							
4. Familiarity	2.88	1.73		.02	.08	.48*						
5. Liking	4.49	.65		−.11*	.19*	.18*	.26*					
6. Reputation	4.49	.92		−.07	.19*	.14*	.19*	.73*				
7. Epistemic uncertainty	3.47	.45	.61	−.12*	.20*	.24*	.11*	.17*	.17*			
8. Aleatory uncertainty	3.25	.51	.74	.12*	−.17*	.10*	.05	−.03	−.06	−.04		
9. Rate of return	.02	.24		−.00	.02	.03	.06	.20*	.17*	.10*	−.02	
10. CAPM beta	.97	.71		−.03	−.01	−.01	−.02	−.04	−.06	−.14*	.02	−.12*

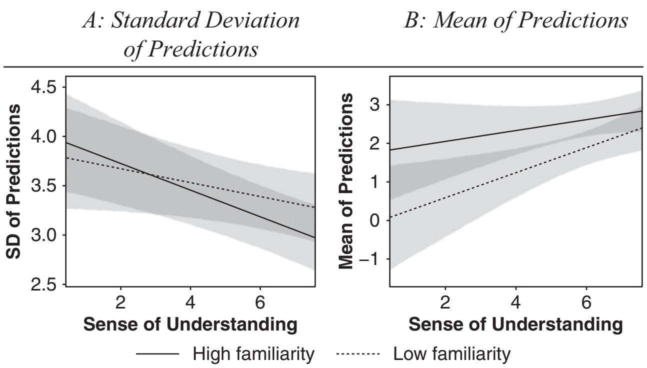
*$p < .05$.
Notes: Statistics were calculated after data aggregation and, thus, N = 443.

To examine the relationships between understanding, familiarity, and risk, we constructed two linear, mixed models, one with mean as the dependent variable and one with standard deviation as the dependent variable. We used familiarity condition (coded −.5 for low familiarity and +.5 for high familiarity), understanding ratings (mean-centered), and their interaction as predictor variables and estimated random intercepts by participant. Figure 2 shows the primary results. Although prediction standard deviations were similar in the high and low-familiarity conditions (Figure 2, Panel A), prediction means were higher in the high-familiarity condition than in the low-familiarity condition (Figure 2, Panel B). In both familiarity conditions, sense of understanding was negatively related to prediction standard deviations (Figure 2, Panel A) and positively related to prediction means (Figure 2, Panel B). This pattern of results suggests that perceived understanding and familiarity have unique effects on perceived risk. Perceived understanding is related to both the standard deviation and mean of performance predictions, whereas familiarity is related only to the mean.

More formally, perceived understanding was negatively associated with prediction standard deviations, on average across the familiarity conditions (b = −.10, t(1,171.90) = −4.10, $p < .001$, $\eta^2 = .02$). The interaction between perceived understanding and familiarity was not significant (b = −.03, t(1,171.90) = 1.29, $p > .19$, $\eta^2 = .002$), indicating that the relationship between perceived understanding and prediction standard deviations did not depend on familiarity. At the mean level of perceived understanding, familiarity did not significantly influence prediction standard deviations (b = −.10, t(97.90) = −.89; $p > .37$, $\eta^2 < .001$). Perceived understanding was positively associated with prediction means, on average across the familiarity conditions (b = .23, t(911.40) = 2.89, $p < .004$, $\eta^2 = .01$). The interaction between understanding and familiarity was not significant (b = −.09, t(911.40) = −1.14, $p > .25$, $\eta^2 < .001$), indicating that the relationship between perceived understanding and prediction means did not depend on familiarity. At the mean level of perceived understanding, familiarity had a significant positive effect on prediction means (b = .36, t(97.40) = 2.29, $p < .025$, $\eta^2 = .01$).

Figure 2

EFFECTS SENSE OF UNDERSTANDING AND FAMILIARITY ON PREDICTIONS



Note: Confidence bands represent the bootstrapped 95% confidence interval of estimates.

In summary, Study 3 showed that familiarity and understanding influence risk perceptions in distinct ways. While higher understanding and higher familiarity were associated with higher prediction means, only higher understanding was associated with less variable predictions. The relationship between perceived understanding and each indicator of risk did not depend on a person's familiarity with the company. These results conceptually replicate past research on the connection between familiarity and risk perceptions (Song and Schwarz 2009) but provide novel insight into the nature of the effect.

STUDY 4: MANIPULATING UNDERSTANDING

Studies 1–3 showed a correlation between sense of understanding and risk perception. The aim of Study 4 was to provide evidence for a causal effect of sense of understanding on perceived risk. For this purpose, we manipulated sense of understanding by providing company information in either a standard format or with the sentences of the description randomly shuffled. This intervention is commonly used in the text comprehension literature to manipulate understanding. People partially understand text based on common structures and the organization of information within the text. Randomizing sentence order breaks these structures leading to diminished understanding (Kintsch, Mandel, and Kozminsky 1977; Larsen 1980; Thorndyke 1977, 1979). Thus, we predict that unstructured information about companies will lead to a diminished sense of understanding, which will in turn lead to higher perceived risk.

Method

Respondents from MTurk (N = 1,000) completed the study for payment. Each participant rated the same eight companies randomly selected from the S&P 500 (Lam Research, Waters Corp., LyondellBasell, KLA-Tencor, Aetna, Pioneer Natural Resources, Sysco Corp., and People's United Financial). Participants were randomly assigned to one of two conditions. For the structured condition, we presented participants with the same company descriptions used in prior studies. For the unstructured condition, we randomly shuffled the sentences of each company description. To maintain coherence, we replaced the first pronoun used to refer to the company with the company's name. The descriptions were otherwise identical. For an example stimulus, see Web Appendix A.

After reading each company description, participants rated their sense of understanding on a four-item scale and perceived risk on an eight-item scale. The scale items and summary statistics are provided in Table 4. The risk scale consisted of four items intended to measure participants' expected performance of the company's stock and four items intended to measure uncertainty regarding performance. These constructs were meant to provide an analogous measurement of the prediction means and standard deviations used in Studies 2 and 3. The order of the scales, as well as the items within the scales, was randomized.

We first conducted exploratory factor analyses on the understanding and risk scales. For the understanding scale, we estimated a single factor using maximum likelihood factoring. The factor analysis revealed high loadings for all items (all loading > .91), as well as high reliability ($\alpha = .96$). For the risk scale, we estimated two factors using maximum likelihood

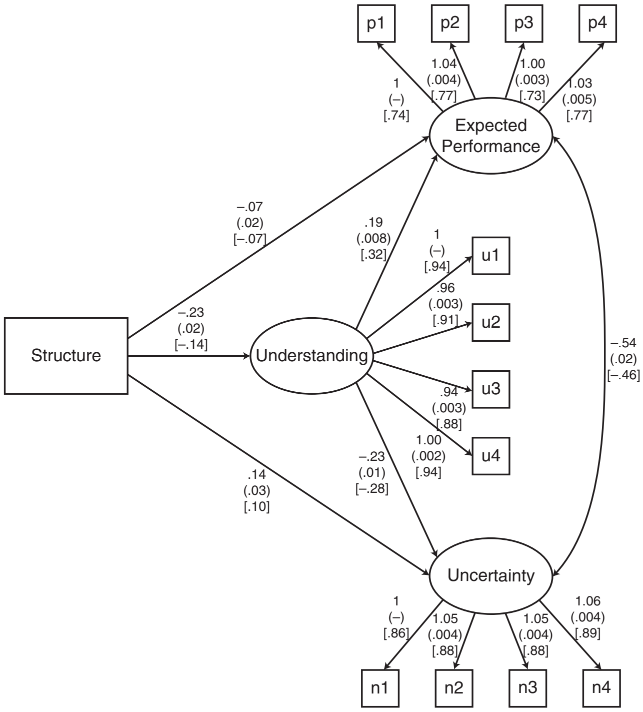
Table 4
SUMMARY STATISTICS AND SCALE ITEMS FOR STUDY 4

	M	*SD*	α
1. Sense of Understanding (1 = "Strongly disagree," and 7 = "Strongly agree")	4.56	1.67	.96
a. I understand what [company] does.	4.70	1.72	
b. I can explain to others what [company] does.	4.49	1.79	
c. I can make sense of the facts I know about [company].	4.37	1.86	
d. [Company]'s business is easy to understand.	4.69	1.73	
2. Expected Performance (1 = "Strongly disagree," and 7 = "Strongly agree")	4.46	1.09	.84
a. It is likely that [company]'s stock will go down in value. (R)	4.37	1.35	
b. [Company]'s stock price is more likely to go up than down.	4.54	1.32	
c. I will probably lose money investing in [company]'s stock. (R)	4.39	1.37	
d. The value of [company]'s stock will increase.	4.53	1.26	
3. Uncertainty (1 = "Strongly disagree," and 7 = "Strongly agree")	4.27	1.45	.93
a. There is a lot of uncertainty regarding how well [company]'s stock will perform.	4.11	1.59	
b. I am unsure whether [company]'s stock will do well or poorly.	4.32	1.63	
c. I feel like anything could happen regarding how well [company]'s stock will perform.	4.31	1.59	
d. It is unclear what the outcome of investing in [company] will be.	4.35	1.59	

	1	*2*
1. Sense of understanding		
2. Expected performance	.29*	
3. Uncertainty	−.28*	−.45*

*$p < .05$.
Notes: N = 1,000.

Figure 3
HYPOTHESIZED STRUCTURAL EQUATION MODEL FOR STUDY 4



Notes: N = 1,000. Paths are labeled with unstandardized estimates, with standard errors in parentheses and standardized estimates in brackets. All paths are significant at the $p < .001$ level.

factoring with oblimin rotation. The factor analysis revealed a factor loading structure matching the two expected constructs. The four expected performance items loaded onto one factor (all loadings > .60), and the uncertainty items loaded onto the second factor (all loadings > .82). All cross-loadings were less than .12. Each subscale also had high reliability ($\alpha_{expectation}$ = .84, $\alpha_{uncertainty}$ = .93). The factors had a correlation coefficient = −.47. Given the results of the factor analysis, we averaged the responses of the three scales to form composite variables for the initial analysis.

Results and Discussion

We conducted three mixed ANOVAs to assess the effect of the structure manipulation on understanding, expected performance, and uncertainty. Removing structure significantly decreased understanding ratings ($M_{structured}$ = 4.78, $M_{unstructured}$ = 4.33; t(998) = −9.47, $p < .001$, d = .35). Removing structure also decreased expected performance ($M_{structured}$ = 4.56, $M_{unstructured}$ = 4.34; t(998) = −6.56, $p < .001$, d = .22) and increased uncertainty ($M_{structured}$ = 4.08, $M_{unstructured}$ = 4.48; t(998) = 7.54, $p < .001$, d = .34).

We assessed our hypothesized mediation relationship using structural equation modeling in the lavaan package in R (Rosseel 2012). Figure 3 shows the hypothesized model. The model examined the mediating relationship of sense of understanding between the structure manipulation (coded −1 = structured, 1 = unstructured) and the two components of risk perception. The model also estimated latent variable intercepts and one residual covariance, between expected performance and uncertainty. We estimated the model using maximum likelihood estimation. Standard errors were clustered by participant to account for repeated measurement. The results indicate a good model fit (comparative fit index = .98; goodness-of-fit index = .99; root mean square error of approximation = .09), and all scale items had high loadings on their respective constructs.

The model also provided strong support for our hypotheses. The structure manipulation significantly decreased understanding ratings (standardized coefficient = −.14, z = −9.47, $p < .001$), and higher understanding ratings were associated with better performance expectations (standardized coefficient = .32, z = 22.81, $p < .001$) and less uncertainty (standardized coefficient = −.28, z = −18.50, $p < .001$). The indirect effects of structure on expected performance (standardized coefficient = −.04, z = −8.82, $p < .001$) and uncertainty (standardized coefficient = .04, z = 8.06, $p < .001$) were also significant, indicating that understanding significantly mediated the relationship between the structure manipulation and the two risk measures.

STUDY 5: PORTFOLIO CONSTRUCTION

Study 5 investigated whether people's tendency to rely on their sense of understanding as a cue for risk affects investment decisions. Participants constructed portfolios for risk-tolerant and risk-averse investors by allocating money across ten companies, half of which were easy to understand and the other half hard to understand. Because people believe that companies they do not understand are riskier, we expected participants would allocate more money to companies that are hard to understand for the risk-tolerant investor compared to the risk-averse investor. Participants were incentivized to create portfolios that matched their clients risk preferences.

We tried to mimic the naturalistic setting consumers find themselves in when making real investment decisions. In addition to company descriptions, participants could view common stock statistics, a chart of past stock returns, and a set of investment analyst predictions and recommendations. This represents all information typically available to consumers on financial services websites. We collected two samples of data—one from MTurk and another from an online investing community—to investigate whether our findings generalize to consumers who have more knowledge about investing, engage with investments more often, and have larger investment portfolios.

Method

Participants (N = 334) completed Study 5 for a base payment plus an incentive-compatible payment described next. We recruited 189 participants from MTurk and 145 participants from an online investment community. In the investment community, members discuss their portfolios, returns, and strategies, and they have general investment discussions on topics related to investment theory, potential stock picks, and trends. Expert participants reported an average portfolio size of $128,000 and bought or sold stocks weekly.

Participants were asked to imagine they were financial advisors and to create investment portfolios for two clients, in a random order. The low-risk-tolerance profile stated, "Ms. S wants predictability from her investments. She doesn't need her portfolio to make a lot of money; she just wants stable returns." The high-risk-tolerance profile stated, "Ms. R wants to invest in a portfolio of stocks that will yield a high return. She is willing to tolerate unpredictability and volatility from her investments. She just wants her investments to make money!" For a replication of this study with different client profiles, see Web Appendix D.

After reading the profile for the first client, participants examined the companies they could invest in. We selected ten companies from the S&P 500 based on the following characteristics. Half of the companies were rated as difficult to understand in Studies 1 and 2 (LyondellBasell, Waters Corp., CME Group, Baxter International, and NiSource Inc.), and half of the companies were rated as easy to understand (ONEOK Inc., Micron Technology, People's United Financial, Merck & Co., and First Energy Corp.). Finally, to control for potential differences in industries across the easy and difficult companies, each difficult company matched the industry of an easy company.

Participants initially saw only the company names displayed on the screen, and they could click on a company to view more information. Participants could choose to view four different kinds of information: a company description, stock statistics (e.g., earnings per share, price-to-earnings ratio, market cap), a chart displaying the previous two years of stock returns, and analyst predictions of stock prices and recommendations. We recorded which information participants chose to view. Participants chose to view the company description 72% of the time, stock statistics 26% of the time, the performance chart 78% of the time, and analyst recommendations 44% of the time. Web Appendix A provides an example stimulus.

After examining the companies, participants allocated $10,000 across the ten companies. Participants then read the profile for the other client and completed the second allocation task. During the allocation tasks, participants could reread the client's profile or further examine the companies. Following both allocation tasks, participants, in a random order, rated their sense of understanding of what each company does on the same scale used in Studies 1–3.

To incentivize performance, participants were informed that they could win an additional $100 if they constructed the best portfolio among all participants for either of their clients, measured three months after the study was conducted. For the high-risk-tolerance client, we defined the best portfolio as the portfolio with the highest overall return. For the low-risk-tolerance client, we defined the best portfolio as the portfolio with the lowest CAPM beta statistic. As a result of a programming error, 50 participants from the MTurk sample did not receive the instructions describing this incentive. Analyses revealed these participants did not significantly differ from the other MTurk participants in terms of portfolio allocations and understanding ratings. The analyses below include these participants.

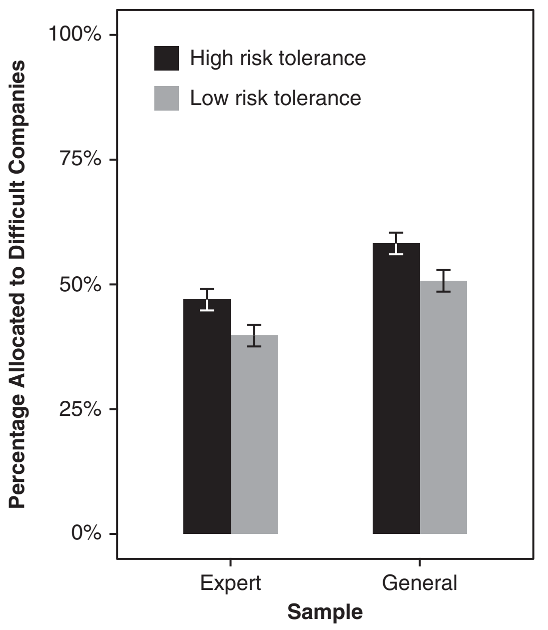
Results

We first examined whether the manipulation of understanding was successful. We averaged the understanding ratings for the five easy- (α = .76) and hard- (α = .74) to-understand companies. As expected, participants gave higher ratings for easy-to-understand companies (M_{easy} = 5.77, M_{hard} = 4.88; t(333) = 20.62, p < .001, d = .95).

For our primary analysis, we examined whether participants allocated more money to difficult companies for the high-risk-tolerance client compared with the low-risk-tolerance client. In addition, we examined whether this effect varied in the expert sample compared with the general sample. We first computed the percentage of money allocated to difficult companies in each portfolio. Figure 4 shows the group means of these allocations. To test statistical significance, we conducted a mixed ANOVA with allocations to difficult companies as the dependent variable and risk tolerance (coded −1 = low risk tolerance, 1 = high risk tolerance), sample (coded −1 = general sample, 1 = expert sample), and their interaction as independent variables. The results revealed a main effect of risk tolerance on allocations (t(332) = 3.86, p < .001, d = .28). Participants allocated significantly more money to difficult companies in the high-risk-tolerance condition (M = 53.33%) compared to the low-risk-tolerance condition (M = 45.96%). Although expert participants allocated significantly less money overall to difficult companies than general population participants (M_{expert} = 43.35%, $M_{general}$ = 54.47%; t(332) = −5.04, p < .001, d = .56), the effect of risk tolerance on allocations did not significantly interact with sample (t(332) = −.07, p > .94). The simple effects of risk tolerance on allocations were significant in both the expert (M_{high} = 47%, M_{low} = 40%; t(144) = 2.38, p < .02, d = .26) and general samples (M_{high} = 58%, M_{low} = 51%; t(188) = 3.13, p < .003, d = .29).

If the effect of risk tolerance on allocation is due to perceived understanding, we should find that the effect is larger for

Figure 4
EFFECTS OF RISK TOLERANCE AND EXPERTISE ON ALLOCATIONS



participants who had larger disparities in their perceptions of understanding for easy and difficult companies. In other words, we should find an interaction between risk tolerance and understanding disparity on allocations. To create a measure of understanding disparity, we subtracted the mean understanding judgments for the five difficult companies from the mean understanding judgments for the five easy companies. This difference score has a possible range of –6 to 6. A score of zero indicates that easy and difficult companies were rated equally. Six indicates that easy companies were rated as much easier to understand than difficult companies. Negative six indicates that easy companies were rated as much harder to understand than difficult companies. We then regressed allocations to difficult companies on risk tolerance, sample, understanding disparity, and all two and three-way interactions. As predicted, participants with more disparate understanding ratings between easy and difficult companies had significantly larger differences in allocations between the two risk tolerance conditions ($b = .07$, $t(330) = 2.92$, $p < .004$). Finally, the three-way interaction, which tests whether the previous two-way interaction was different across the two samples, was not significant ($b = -.02$, $t(330) = -.56$, $p > .57$).

Discussion

Study 5 showed that sense of understanding affects portfolio construction. Because sense of understanding is not an ecologically valid cue for risk (see Studies 1 and 2), relying on it can lead to miscalibrated beliefs about risk exposure. For instance, someone approaching retirement may unknowingly take a high-risk gamble on her retirement savings by investing in companies she feels she understands well.

Study 5 also revealed that a greater sense of understanding does not necessarily increase preference. Prior research has found that consumers tend to prefer products they feel they understand (Fernbach, Sloman, et al. 2013; Hadar, Sood, and Fox 2013; Jhang, Grant, and Campbell 2012). We found that this is true for investments when risk tolerance is low. However, when risk tolerance is high, people prefer to invest in companies they feel they do not understand well.

Finally, Study 5 extended our prior findings in two important ways. First, the relationship between sense of understanding and risk perception is robust to having additional information available on which to base decisions. Participants had access to and examined a wide variety of information. However, participants tended to examine company profiles, and their level of understanding of those profiles affected their investment choices. Second, the relationship is also robust to investor expertise. Experienced investors from the online investment community used their sense of understanding of companies to determine investment choices in a similar manner as participants from the general population. In addition, expert investors tended to invest more money in companies they feel they understand better. This may reflect the prevalence of the "invest in what you know" strategy among more active consumer investors.

GENERAL DISCUSSION

We found that having a high sense of understanding of what a company does affects simple ratings of perceived risk (Study 1) as well as predictions of future stock performance (Study 2). When people feel they understand a company, prediction distributions have smaller standard deviations and higher means, implying that people are more certain about their predictions and believe the stock will perform better. While sense of understanding affects perceived risk, it does not correlate with objective risk, and thus, it is not a valid cue for investment risk. We also showed that the effect of understanding is not due to familiarity with the company (Studies 1–3), that presenting the same information in a different format can alter both sense of understanding and perceived risk (Study 4), and that the effect of understanding on perceived risk affects downstream investing behavior (Study 5).

Our article has several limitations that offer opportunities for future research. First, we presented participants with neutral information from a single source. However, investors often acquire information from a variety of sources over time, and this information can be positive or negative. New information affects both subjective understanding and objective understanding. While this article examined the role of subjective understanding, future research could investigate the interaction of both. For instance, a person may initially think that Starbucks is an easy-to-understand company and thus perceive low risk. New information about the company may reveal an unknown complexity and decrease people's sense of understanding. Our studies suggest that this should increase perceived risk. However, the new information may also affect people's objective understanding, and if the new information is positive, it might decrease perceived risk. The combination of changes in subjective and objective understanding may imply that the relationship between information acquisition and perceived risk is nonlinear. It would be interesting to explore if this nonlinearity varies across products, firms, or industries.

Second, our article does not explicitly test the process that causes understanding to influence risk perception. We proposed that understanding decreases uncertainty because people perceive that they have better mental models that allow them to make more precise predictions. In addition, we proposed several ways that understanding may increase expected performance, including by inducing positive affect. Future research can explore these possibilities to better determine the mechanisms of the relationship between understanding and risk perception.

Third, the mechanisms at work in these studies are likely at work in a variety of other kinds of investment decisions besides company stock. Future research could investigate how understanding affects broader portfolio construction. For instance, individual companies may be viewed as easier to understand than index funds, which are in turn viewed as easier to understand than exchange-traded funds. These perceptions may lead investors to overweight some classes of investments. Such research may provide novel insights into suboptimal investment decisions. For instance, previous research has shown that people tend to allocate a large percentage of their 401(k) savings to stock in the company they work for compared with mutual funds, which offer more safety (Benartzi 2001). One potential explanation is that people feel they understand their company, while people feel they do not understand how specific mutual funds work, leading to miscalibrated risk perceptions.

Furthermore, managers often make risky decisions about where to invest firm resources. Should research and development money be allocated to complex, experimental ideas or simple projects? Should the firm expand into new marketplaces or focus on existing markets? Should the firm launch a new product line or improve a current one? Much like consumers' investment decisions, managers' decisions are heavily affected by risk perceptions (March and Shapira 1987). Future research could investigate the extent to which managers' risk perceptions are affected by their sense of understanding of their various options.

Fourth, it may be interesting to explore how judgments of understanding and risk affect other areas of consumer financial decision making. When selecting health insurance, consumers are often faced with several options that vary among dozens of parameters. They need to minimize expected out-of-pocket expenses, weighing both chance events of catching illnesses and certain expenses, such as physical examinations. Some policies include a deductible, copays, and coinsurance, while others include just copays. Some policies let patients see any doctor for any illness, while others restrict patients to a network of care providers or limit coverage for certain illnesses. It seems possible that consumers view more easily understood insurance policies as less risky, regardless of the nature of the coverage.

Finally, a common alternative to the "invest in what you know" advice is to give consumers simple decision rules to follow such as "invest in a diversified portfolio" or "invest in passively managed mutual funds" (Thaler 2013). While developing the level of objective understanding necessary to make accurate valuations of companies may be beyond most consumers' resource constraints, simple decision rules appear to offer a solution. However, a consumer's sense of understanding about the rules may influence how (s)he follows them. For instance, consumers tend to misunderstand the consequences of diversification (Reinholtz, Fernbach, and De Langhe 2016) and may misapply the rule. Even those who understand a specific rule may be unlikely to follow it. Prior research has shown that people are more likely to defect from decision rules when they have more expertise in an area because they think they can outperform the rule (Arkes, Dawes, and Christensen 1986). Future research can investigate the different ways understanding influences decision rule use in the financial domain and determine whether offering simple decision rules is a better intervention for improving consumer investment decisions than developing an objective understanding of investments.

By using their sense of understanding to judge the riskiness of stocks, consumers can make two errors. First, they can perceive high risk in a poorly understood company, when really the company has low risk. Second, they can perceive low risk in a well-understood company, when really the company has high risk. The implications of the two errors are not equal. With the first error, a consumer may pass up a good, low-risk investment or, alternatively, take on less risk than (s)he initially desired. While neither is ideal, the consumer at least thinks (s)he is making a risky investment and likely has planned for potential negative outcomes. However, if a consumer is trying to invest in what (s)he knows, (s)he will be more likely to make the second error, because that involves investing in a company (s)he feels (s)he understands. Here, (s)he may invest a significant amount of money in what (s)he thinks is a low-risk, well-understood investment and may be unprepared for the consequences associated with high-risk investments. Thus, the common advice to "invest in what you know" poses a unique risk to consumers partially because of how the advice is misinterpreted. The challenge is then not to get consumers to follow the advice, but to get them to understand the advice.

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