The Influence of the Phonetic Elements of a Name on Risk Assessment

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The authors propose that the phonetic elements of a name affect risk perception. Specifically, they find that people prefer a name that evokes volatility when faced with a risky prospect, but prefer a name that evokes calmness when faced with a safe prospect. The authors posit that a volatile (vs. calm) prospect name results in more perceived fluctuations, and thus greater movement from, the given risk level. Therefore, a volatile prospect name results in a wider range of probabilities compared to a calm prospect name. The authors test the proposed effect and the role of the phonetic elements of a name using real-world data and controlled studies within diverse consumer domains (e.g., product evaluations, wagering, and branding). Findings contribute to the larger theoretical area of phonetic symbolism and provide guidance for practitioners trying to maximize preference for a given product, service, or policy.

Keywords: decision-making, linguistics, phonetic symbolism, risky prospects, probability, phonetic score

Imagine a novice investor who is deciding to invest in one of two stocks. The challenge is that the two stocks are equivalent on all objective risk criteria of loss or gain, except for their name. One is called *Maluma*, and the other *Taketa* (adopted from Lindauer 1990). Which of these two stocks might the investor prefer? Normative theory would predict indifference on the investor's part, as success and failure are statistically equiprobable. However, utilizing the findings in phonetic symbolism, we predict that preference for the stocks would be influenced by their names. Phonetic symbolism has demonstrated that the phonetic elements of a name can change the perception of a named entity (Imai and Kita 2014; Klink 2000; Lakoff and Mark 1980). The phonetic elements can be front and back vowels, consonants, rhythm, turbulence, sequence, and closed vowel sounds, among others. These elements change one's perception of a name by inadvertently conveying particular attributes about the name, such as aggressive, peaceful, sharp, rounded, fast, and slow (Imai and Kita 2014; Lindauer 1990; Klink 2000; Köhler 1929; Lakoff and Mark 1980; Lowrey and Shrum 2007; Pogacar, Shrum, and Lowrey 2018; Ramachandran and Hubbard 2001).

In this research, we propose that a specific attribute evoked by the phonetic elements of a name—volatility—affects risk assessment. That is, a given risk level (e.g., 60% chance of success) would be perceived differently if associated with a name that evokes more volatility compared to one that evokes less volatility. Specifically, among risky prospects, people would prefer more volatile names; however, among safe prospects, they would prefer less volatile names. In our introductory investing example, if *Taketa* is perceived as more volatile than *Maluma* because

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of its phonetic elements, then the novice investor might prefer *Maluma* over *Taketa* when risk is low, but prefer *Taketa* over *Maluma* when risk is high. We next discuss past work relevant for our proposed effect and begin with clarifying a few terms used throughout the article.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

Terms

We define *prospect* as an option that yields a certain outcome with a known probability (Tversky and Fox 1995; Tversky and Kahneman 1974). Specifically, a *risky* prospect has a lower probability of yielding an outcome, while a *safe* prospect has a higher probability. Second, consistent with past work, we define *volatility* as a tendency to change unpredictably from a stable state. For example, volatile stocks are characterized by fluctuating stock prices. Statistically, volatility can be understood as greater dispersion, and is calculated using variance or standard deviation from the mean; wider swings from the mean would represent greater volatility. In our context of evaluating risky and safe prospects, volatility represents fluctuations away from the given levels of risk that turn risk from a point estimate to a range. If a prospect is perceived as more volatile, it would have greater fluctuation around the given risk level. That is, the range of probabilities associated with it would be wider. We refer to this range of probabilities as a *probability band*. Third, we refer to our dependent variable as *evaluations*. We capture evaluations for a prospect through such measures as wagering amount, compliance, and value.

Finally, departing from past research that has generally focused on isolating the influence of a single phonetic element on people's evaluations, we investigate how the many naturally occurring phonetic elements of a name (front and back vowels, consonants, rhythm, turbulence, sequence, closed vowel sounds, etc.) can, in totality, evoke volatility and influence evaluation of risky versus safe prospects. A detailed description of our method to assess volatility of a name is presented after the theoretical review.

Decision-Making Under Risk

Decision-making under risk involves the evaluation of prospects that yield an outcome with a certain known probability. In order to evaluate such prospects, people have been known to use information in the environment, even if it is irrelevant (Brainerd and Reyna 1990; Tversky and Kahneman 1974). For example, prior research has revealed a number of factors that—despite having no influence on the objective probability of a prospect—have been shown to influence evaluation of risky versus safe prospects. This includes factors such as changes in wordings (Tversky and Kahneman 1986), perceived self-efficacy in unrelated tasks (Krueger and Dickson 1994), accessibility of events in memory (Kusev et al. 2009), positive affect (Isen, Nygren, and Ashby 1988), fear versus anger at the moment of decision-making (Lerner and Keltner 2001; Loewenstein et al. 2001), the number of simultaneous options displayed (Stewart et al. 2003), and the base rates used to convey probability (e.g., X out of 100 vs. X out of 1,000; Yamagishi 1997). In our research, we examine one such type of irrelevant information—phonetic elements of a name.

Phonetic Elements and Meaning of Words

Each word consists of individual sounds emanating from phonetic elements that come together—and are experienced holistically—as the sound of that word (Hinton, Nichols, and Ohala 1994). For example, phonetic elements can be the number of consonants or vowels, the type of vowels, whether the vowel is front (e.g., *feel*) or back (e.g., *tool*), and a fricative or affricative sound (Imai and Kita 2014; Klink 2000; Lakoff and Mark 1980). The phonetic elements determine how a word is experienced by human senses, and add meaning to the word over and above its connotation (Lindauer 1990).

Since Plato's Cratylus dialogue, research in phonetic symbolism has shown that words have systematic relationships to certain meanings like the perception of a word's physical attributes (Bredin 1996; Imai and Kita 2014). For example, words with front-vowel sounds—which are high in pitch and frequency[1] (e.g., the *ee* sound in *three*, the *ih* sound in *fit*)—are often associated with smallness (Sapir 1929), hardness (Koriat and Levy 1977), brightness (Newman 1933), and angularity (Köhler 1929). Such an association between phonetic elements and attributes makes people associate the name *Kiki* with a sharp object; conversely, the name *Bouba* is associated with a rounded object (Köhler 1929; Ramachandran and Hubbard 2001). For consonants, letter sounds produced by air friction when enunciated are associated with being smaller, faster, and lighter than letter sounds with hard stops or closure of the mouth (Klink 2000; Ohala 1994).

Marketing literature has documented many instances of the impact of attributes evoked by the phonetic elements of names on consumer judgments and evaluations. For example, participants perceived a brand of dark beer as stronger, darker, and heavier—and rated it higher—when the name used a deeper vowel sound (e.g., *Dotil* vs. *Detil* [Klink 2003]). Lowrey and Shrum (2007) have documented that vowels with quicker and sharper (vs. deeper, lower) sounds equated to a greater preference for a sportier, speedier

1 By contrast, back-vowel sounds are deeper in pitch and frequency (e.g., the *ooh* sound in *two*).

convertible (vs. a sport-utility vehicle) and a sharp knife (vs. a blunt hammer). However, this preference reversed when the name was changed to a lower, deeper vowel sound, with participants then opting for the slower, larger sport-utility vehicle and the duller, blunted hammer. Words with back vowels (e.g., *floog*) elicited abstract construal, while words with front vowels (e.g., *fleeg*) elicited concrete construal (Maglio et al. 2014). People were shown to be willing to pay more for brand names with consonant sequences that move from the back to the front of the mouth (e.g., a nonsense name such as *kadap*) rather than in the reverse order (e.g., *padak*) (Topolinski, Zürn, and Schneider 2015). An ice cream brand named *Frosh* was considered more rich, creamy, and smooth than the same ice cream named *Frish* (Yorkston and Menon 2004).

Phonetic elements of names can activate two types of attributes. Phonetic elements could evoke physical attributes such as big/small and sharp/dull, as discussed previously (Lakoff and Mark 1980; Lowrey and Shrum 2007). Phonetic elements could also evoke psychological attributes. A word with a lower-frequency sound could convey aggressiveness, unpredictability, dominance, and assertiveness, while higher frequencies could convey politeness, calmness, and subordination (Klink 2000; Ohala 1994). For instance, *Taketa* was considered to be more assertive and aggressive compared to *Maluma*, which was considered more peaceful and friendly (Lindauer 1990). Therefore, a name, which by itself has no meaning, could evoke psychological attributes due to its phonetic elements. In sum, past findings show that the phonetic elements of a name (e.g., the use of a fricative or deeper vowel sound) evoke attributes (e.g., dark, aggressive, calm, heavy) that influence subsequent evaluations of objects with such names.

Hypotheses

Existing research has demonstrated that phonetic elements of a name can evoke different physical and psychological attributes. Utilizing this research, we propose that the phonetic elements of a name have the ability to evoke the construct of volatility. Evoked volatility, in turn, affects the perception of the given risk level. Therefore, a volatile name will result in greater fluctuations—while a calm name will result in lower fluctuations—from the given risk levels. Since greater fluctuations result in a wider probability band irrespective of prospect risk, volatile prospect names would result in a wider probability band, whereas calm prospect names would result in a narrower probability band.

Moreover, past work has suggested that a risky prospect results in a greater inclination to seek gains, whereas a safe prospect results in a greater inclination to avoid losses (Atkinson 1957; Kahn and Meyer 1991). We suggest a similar effect for names. Specifically, a wider probability band allows a perception of higher possible gains; hence, volatile prospect names will be preferred for risky prospects when people are seeking gains. However, a narrower probability band allows a perception of avoiding losses; thus, a calm prospect name will be preferred for safe prospects when people are trying to avoid losses.

We explain with an example. Consider a risky prospect with a low chance of winning (e.g., 10%). If it has a volatile name, the name would make the probability band appear wider (e.g., 1% to 20%) than that of a calm name (e.g., 7% to 13%). Which name appears to provide a greater chance of winning? The best chance of winning with a volatile name is 20% (which is the high end of the probability band); but, with a calm name, the best chance appears to be only 13%. Thus, we posit that as the probability band widens with a volatile name, people would prefer a volatile name for a risky prospect. Similarly, when we consider a safe prospect with a high chance of winning (e.g., 90%), a volatile name would make the probability band appear wider (e.g., 80% to 99%) than a calm name (e.g., 87% to 93%). The worst chance of losing with the calm name is 13%, whereas the worst case for the volatile name increases to 20%. Thus, we posit that as the probability band narrows with a calm name, people would prefer the calm name for safe prospects. Therefore, we propose the following two hypotheses:

> **H1:** Among risky prospects, people will prefer prospects with volatile names, while among safe prospects, they will prefer prospects with calm names.
>
> **H2:** Volatile names will make the probability band appear wider compared to calm names.

We conducted three studies that directly test for hypothesis 1. We used data from the Kentucky Derby (study 2) to assess whether horses with volatile names showed greater wagering amid risky prospects, and whether those with calm names showed greater wagering activity amid safe prospects. Study 3 replicated study 2 in a controlled setting using simulated horse racing. In study 4, we explored a negative domain and examined the influence of the phonetic scores of hurricane names on compliance (using storm fatalities as the dependent measure).

Study 5 provided a direct test of hypothesis 2 by examining whether volatile names resulted in a wider probability band and calm names resulted in a narrower probability band. In study 6 we tested our theory by examining whether a wider (or narrower) probability band mediated the influence of volatile (or calm) prospect names on evaluation of risky and safe prospects. In study 7, instead of measuring perceived volatility, we manipulated volatility orthogonally by making the construct of volatility versus calmness accessible in participants' minds; we then examined the influence of volatile (or calm) prospect names on preference. We also tested for alternate accounts in studies 1, 5, and 6.

oh no....

Estimating Volatility Due to Phonetic Elements

If we consider just one phonetic element of a word, testing for its influence is straightforward. This is because it involves just two conditions—when the phonetic element is present versus when it is absent—and controls for all other phonetic elements. Artificially created names used in past research allow for such testing; for example, words might differ by a deeper versus lighter vowel sound (e.g., *Frosh* vs. *Frish*) that changes only one element (e.g., *o* vs. *i*; Yorkston and Menon 2004). However, in the marketplace, names do not vary on just one phonetic element—that is, there are many elements that differ between two names. Therefore, to understand how people's evaluations change for different names, we could not use this simple dichotomous approach that examines the presence versus absence of a specific phonetic element.

One possibility is to give the presence or absence of a specific phonetic element a score, which could then be combined across various elements to form the phonetic score of a name. One scoring method that takes into account several such phonetic elements, and assigns a numeric value to each element, was proposed by Smith (1998). Based on such factors as syllables, rhythm, and vowel and consonant placement, a name would receive higher or lower phonetic score. For example, a name with just two syllables receives +1.5 as a score, a high vowel occurring before a terminal fricative receives a score of –1.0, a terminal nasal receives a +1.5, while an ending fricative receives a –1.5 score. Scores given to each of the phonetic elements are summed to provide a phonetic comfort score for the name. A high phonetic score is considered to evoke the attribute of comfort, while a low phonetic score is said to evoke discomfort. Web appendix A1 provides details of the scoring method, and web appendix table A2 provides a review and comparison with competing methods. Web appendix table A3 shows how the phonetic elements used in Smith's (1998) scoring method pertaining to the attribute of volatility are consistent with the way that these phonetic elements have been discussed in past research.

Smith (1998) used the scoring method to demonstrate that within different political elections, the candidates with surnames that were higher (vs. lower) on phonetic score were more likely to receive a greater share of the popular vote (Smith 1998, 2007). The scoring method and its findings have been much discussed (Garrett 2010; Hosman 2002; Kuehnl and Mantau 2013; Lowrey and Shrum 2007; Martin 2007; Slovic et al. 2007).

We propose that names that receive a low phonetic score would be considered more volatile than those that receive a high phonetic score. Smith (1998) has demonstrated that a low phonetic score is associated with discomfort, while a high phonetic score is associated with comfort. Extending this, we propose that comfort can specifically convey relaxation and, hence, calmness. Discomfort, on the other hand, can convey instability and unpredictability, indicating volatility. Since past work has not empirically established this association of low (high) phonetic score with volatility (calmness), we do so in study 1. Subsequently, we use this score as a measure of volatility or calmness of a name. Such an approach of measuring volatility allowed us to use real names from the marketplace in our empirical investigation, thus increasing the real-world applicability of our findings.

While we refer to each name as a *volatile name* or *calm name*, we do not imply that volatility is a dichotomous construct. Instead, we consider volatility to be a continuous measure and empirically establish that names receiving lower phonetic scores are perceived to be more volatile, while names receiving higher phonetic scores are perceived to be calm. We refer to Smith's (1998) phonetic comfort score as *phonetic score* for ease of exposition.

Cool!

STUDY 1: RELATIONSHIP BETWEEN PHONETIC SCORE AND VOLATILITY

The main aim of study 1 was to test whether phonetic score captures volatility evoked by a name. To test for this relationship we adopted a four-stage approach, which we detail in the sections that follow.

First Stage: Volatility Scale Items

In the first stage, we recruited 103 participants from a university participant pool who received partial course credit. Participants were randomly assigned to either a volatility or calmness condition. Similar to free-association tasks used in extant research (Aaker 1997; Okazaki, Mueller and Taylor 2010; Paharia et al. 2011; Sung et al. 2015), those in the volatility condition were asked to think about the construct of volatility and to "take a couple of minutes to type all traits or attributes that come to mind when thinking about the word 'volatility.'" Conversely, those in the calmness condition responded to a similar question, with the word changed to "calmness." All participants were asked to rank the words based on how well they captured the given construct. From the listed words, we picked the top 10 that were listed as best capturing volatility (e.g., risky, uncertain, volatile) as well as the top 10 that best captured calmness (e.g., safe, certain, calm). Using these 20 words, we created a 10-item, seven-point bipolar volatility scale where a high (low) score denoted volatility (calmness). Web appendix B includes these scale items and their scoring method.

One could argue that the volatility construct, measured through the volatility scale, might also be capturing related constructs such as perceived aggressiveness, intensity, and drive to win. However, these constructs would not predict our focal hypothesis (hypothesis 1) because people are likely to prefer names that appear aggressive or convey drive to win for both safe and risky prospects. Nevertheless, from a scale development perspective we assessed whether the volatility scale discriminated between volatility and the related constructs.

Second Stage: Discriminant Validity

We followed the process suggested in past work to establish discriminant validity for scales that measure constructs that are not chronic traits (Sweeney and Soutar 2001; Westbrook and Oliver 1991). Two hundred eight Amazon Mechanical Turk (MTurk) participants were asked to recall and describe an object or event that was likely to change suddenly and unexpectedly, without warning, in a direction that could not be determined, and whose magnitude fluctuated a lot. We did not use volatility scale-item words in our description.

In order to assess discriminant validity of the volatility scale, we asked participants to rate the recalled object or event on the 10-item volatility scale as a well as a nine-item scale that captured the related constructs. The related constructs of aggressiveness and drive were captured via items such as aggressive–docile, in-your-face–amenable, pushy–compliant, antagonistic–affable, motivated to win–not motivated to win, competitive–indifferent, scrappy–submissive, and intense–mild. Five participants provided incomplete responses; hence, the data from 203 participants was used in the analysis. The results indicated a high correlation among the volatility-scale items (Cronbach α = .89). The nine-item scale capturing the constructs of aggressiveness and drive was also highly correlated (Cronbach α = .85).

To assess discriminant validity, the data was analyzed using the heterotrait-monotrait (HTMT) ratio of correlations criteria (Henseler, Ringle, and Sarstedt 2015; Pluess et al. 2018), which is derived from the classical multitrait-multimethod (MTMM) matrix (Campbell and Fiske 1959). The HTMT ratio is the ratio between the geometric mean of heterotrait-heteromethod correlations (i.e., the correlations of items across constructs) and the geometric mean of the monotrait-heteromethod correlations (i.e., the correlations of items within the same construct). The HTMT approach helps in establishing the presence or absence of discriminant validity through a threshold; values below .85 indicate the presence of discriminant validity (Hair et al. 2016; Voorhees et al. 2016). The HTMT ratio provides a more conservative test than previously suggested criteria that do not reliably detect the lack of discriminant validity (Voorhees et al. 2016).

The analysis revealed an HTMT ratio (of volatility to aggressiveness/drive scales) of .64—that is, a value below the suggested .85 threshold. Therefore, the second stage established the volatility scale's ability to discriminate volatility from the aggressiveness/drive construct.

Third Stage: Construct Validity

The third stage was designed to measure the construct validity of the volatility scale (Clark and Watson 1995; MacKenzie, Podsakoff, and Podsakoff 2011) and whether the scale items truly captured volatility and calmness. One hundred ten student participants—a different set of participants from the prior stages—took part for partial course credit and were randomly assigned to a volatility or calmness condition. Participants in the volatility condition were shown a series of animated visuals of volatile activities or outcomes: a highly erratic stock return chart, a series of wide-ranging and unpredictable emojis, a developing lightning storm, a rapidly igniting matchbook, inconsistent velocity and angles of pendulums, a rough water current, and a series of rapidly changing random numbers and patterns (see web appendix C). Conversely, those in the calmness condition were shown calm visuals of the same activities or outcomes: a stable stock return, consistently mild emojis, serene weather, an ambient tea candle flame, consistent pendulum velocity and angles, calm water, and a consistent number sequence with a smooth pattern. After seeing each image, participants were asked to rate the image on the 10-item volatility scale.

The results indicated that the volatile images were rated as significantly more volatile than the calm images on the volatility-scale items ($M_{\text{volatile images}} = 4.44$ vs. $M_{\text{calm images}} = 2.85$; $t(108) = 9.68$, $p < .001$, $d = 1.85$). We also conducted a factor analysis and found that the 10 items loaded onto one factor, indicating that the items were measuring the construct of volatility. Cronbach alpha for the 10-item scale averaged .93 for each of the seven visuals (with $\alpha = .99$ for the 10-item scale when averaged over the seven visuals), indicating that the items were reliably measuring volatility.

Fourth Stage: Volatility Scale and Phonetic Score

The main aim of the fourth stage was to examine the relationship between the phonetic score of a name and its perceived volatility. We recruited a different set of participants—195 students taking part in return for partial course credit—who were presented with eight names at random from a list of 110 names varying (and normally distributed) on phonetic score (e.g., phonetic score ranged from –4 to 3, $M = .24$, SD = 1.37). Participants were instructed to carefully read the name(s) presented to them and to say the name(s) to themselves a few times, ostensibly to increase memorability for later use in the survey (a rehearsal approach; Coulter and Coulter 2010). Participants were asked to rate each of eight names on the volatility scale based on how it sounded to them. The results of a repeated-measures mixed model indicated that lower (higher) phonetic scores—that is, volatile (calm) names based on their phonetic score—predicted greater (less) perceived volatility among participants ($\beta_{phonetic\ score} = .04$, $z(1364) = 2.62$, $p = .009$).

In this fourth stage, we also tested for an alternate account based on ease-of-pronunciation influencing risk. One could argue that our proposed effect emerges not because of evoked volatility from the phonetic elements, but from the ease of saying a name. For instance, Song and Schwartz (2009) suggest that novel stimuli are perceived to be less risky if they are easy to pronounce (e.g., a made-up name like Magnalroxate) compared to when they are hard to pronounce (e.g., Hnegripitrom). Ease of pronunciation was perceived to be more fluent, resulting in higher liking for the name and lower risk perception. This alternate argument would assume that calm names are easier to say than volatile names. Importantly, the theoretical predictions from an ease-of-pronunciation account would be very different from hypothesis 1. First, this alternate account would predict a main effect: easy-to-pronounce names would be considered less risky and would always be preferred. Conversely, we predict an interaction where a volatile name is preferred for a risky prospect and a calm name for a safe prospect. Second, ease of pronunciation results in perceiving an entity to be more or less risky—that is, no risk level is provided. We, on the other hand, provide the exact same risk level (e.g., 10% chance of winning) and change the name of the prospect and propose that the name would change the probability band around the given risk level. Third, we focus on phonetic elements that use consistent rules (e.g., front vs. back vowels, fricatives vs. plosives) rather than subjective assessments of ease of pronunciation (as differentiated by Pogacar et al. 2018). Moreover, research on ease of pronunciation does not examine which phonetic elements of a name would make the name easy versus hard to pronounce. Fourth, our effect emerges for both novel as well as familiar names, while past work is confined to novel names. Fifth, our effect emerges for real-world names rather than synthetic names.

Nevertheless, to empirically test for this alternate account, two additional items were included along with the 10-item volatility scale. One captured fluency (fluent or disfluent) and the other captured ease of pronunciation (easy vs. hard to pronounce). The results indicated no effect of phonetic score on these two scale measures ($p = .284$ for fluent; $p = .689$ for ease of pronunciation). The results indicate that phonetic score captured the perceived volatility of the names but did not affect fluency or ease of pronunciation. Therefore, names with a low (high) phonetic score are perceived as more volatile (calm).

STUDY 2: KENTUCKY DERBY DATA

We propose that people will prefer volatile names for risky prospects and calm names for safe prospects (i.e., hypothesis 1). We tested our proposed effect in the horse racing industry, where names are an integral factor in the description of the prospect. Importantly, while the name of each horse is featured prominently, it does not carry any objective information about the horse's ability to win the race.

We used data from the Kentucky Derby from 1999 to 2014. The amount wagered on a horse served as the proxy for the dependent variable of evaluation. The probability of a horse winning or losing—referred to as *odds* in horse racing—served as our measure of prospect risk. Specifically, we predicted that bettors would wager on a horse with a volatile name when its odds suggest a low probability of winning (this risky prospect is also called a *long shot* in horse racing). Conversely, bettors would wager on a horse with a calm name when its odds suggested a high probability of the horse winning (a safe prospect, also known as the *favorite*).

Prior research has described horse racing as similar to investments in the stock market, as bettors/investors try to maximize profit by identifying market efficiencies (Hausch, Ziemba, and Rubinstein 1981).[2] Importantly, rules preclude horses from racing in the Derby more than once, as this particular race assembles only three-year old thoroughbreds; thus, prior Derby performance is not a concern affecting current bets. In addition, all names are unique; industry rules prevent duplication of both recent and well-known historical horse names. These names can be no more than 18 characters (including punctuation and spaces) in length, providing us with a consistent format. Finally, copyrighted names or controversial or profane names are not permitted.

Data and Procedure

We obtained data for the Kentucky Derby, held annually on the first Saturday of May at Churchill Downs in Louisville. The Kentucky Derby is the world's largest thoroughbred racing event, generating approximately US$187 million in wagering (Downs 2014) and more than 15 million viewers (NBC Sports Group 2014) at the time of data collection. In addition to its depth of data, this event has relatively broad public appeal extending beyond horse enthusiasts, thus yielding a good mix of experienced and novice bettors.

The available data spanned 13 Kentucky Derby races between 1999 and 2014. This reflected the full data made available by the vendor at the time of purchase that captured 15 key measures for each of 16–20 unique entries competing within this annual race.[3] The data included the horse's name; two variables reflecting its projected odds of winning (both on the morning of the race and immediately

2 Prior research has tested theories in the sports domain—for example, loss aversion in golf (Pope and Schweitzer 2011) and status bias in baseball (Kim and King 2014).

3 Past performance data was not made available for the 2001, 2006, and 2007 Kentucky Derby races.

before the race itself); the horse's position at the starting line for the race; four historical performance/earnings measures for the horse; and three measures each for the jockey, its trainer, and the horse's owning entity.

We first calculated the phonetic score of each horse name based on our scoring method. Phonetic score was normally distributed (M = –.06, SD = 1.39) and ranged from –4.0 to +3.0 within the data. In order to measure the dependent variable of evaluation we used two variables to assess the bettors' wagering activity for a given race: the odds of winning as projected on the morning of the race, and the odds of winning immediately before the race begins. We refer to these variables as *opening percent* and *closing percent*, respectively.

Opening percent reflects the initial projected probability of winning for each horse in a given race. This probability is based on the originally posted odds as calculated by odds-makers in order to foster anticipated wagering activity of the general public. In horse racing, this probability is presented in an odds-ratio format (e.g., 9-to-1 reflects the expectation of the number of losses to wins for a horse). For ease of interpretation, we convert this ratio to a percentage that indicates a horse's chance of winning. Therefore, 9-to-1 odds indicate a 10% probability of winning. Our closing percent variable can be interpreted similarly; the only difference is that this variable experiences upward or downward drifts depending on the day's actual wagers and is finalized immediately before each race. For example, if actual wagers exceed expected wagers for a given horse (from the time of the original odds being posted to the time of the race), its odds would improve; for example, odds might go from 9-to-1 to 4-to-1. In this example, the probability of winning for this horse as reflected by closing percent would increase from 10% to 20%. Conversely, for less-than-expected wagering on a horse, odds could go from 9-to-1 to 19-to-1, which would indicate a reduction in closing percent from 10% to 5%.

Justification Missing

Control Variables

We controlled for 12 additional variables. First is the starting position of the horse, which reflects not only its position at the starting gate but also the order in which the name appears in race-related materials. We also obtained several historical performance-related variables. We began with past performance measures, consisting of four measures for each horse's lifetime performances leading up to the Kentucky Derby. These measures include the number of first-, second-, and third-place finishes, as well as the horse's prior lifetime earnings (in dollars). Data also included three jockey performance variables accounting for the current race season's results. With many jockeys riding many horses in a given race season, their performance in the current race season was accounted for in terms of the number of their first-, second-, and third-place finishes. We included this as a control given that these factors could sway a bettor's wagering activity. Similar to the jockey measures, we controlled for trainer performance, which reflects the number of first-, second-, and third-place finishes for the trainers of the horses. Finally, to control for the possibility that some owning entities may be held in high regard in the industry, we included an owner control variable.

Model

Given the nested nature of our data with opening odds estimates (level 1) nested within races (level 2), we specify random intercepts for the level 1 and level 2 units. We use a hierarchical (multilevel) mixed-effects linear regression model to predict the percent chance of winning at post time (closing percent) as a function of the phonetic score of the horse's name, the horse's percent chance of winning at the opening of wagers (opening percent), and the interaction of these two variables. We then extend this model to account for the 12 control variables previously noted, including the horse's starting position and past performance and information on jockeys, trainers, and owners. We follow Baayen, Davidson, and Bates (2008) and Boksem and Smidts (2015) in reporting the results.

Results and Discussion

Max change is like 1.5%

The results indicated significant main effects for phonetic score and opening percent, with a significant phonetic score × opening percent interaction. Recall that opening percent is an operationalization of risky and safe prospect; if opening percent is low then it is a risky prospect, and if opening percent is high then it is a safe prospect. The main effect of phonetic score indicates that a one-unit increase in phonetic score results in a .58 reduction in closing percent ($\beta_{\text{phonetic score}} = -.58$, $z = -2.17$, $p = .030$), all else being equal. Moreover, a one-unit increase in opening percent results in a .32 increase in closing percent ($\beta_{\text{opening pct}} = .32$, $z = 2.56$, $p = .011$). The significant phonetic-score × opening percent interaction ($\beta_{\text{phonetic score} \times \text{opening pct}} = .12$, $z = 3.74$, $p < .001$) indicates differences in closing percent between calm and volatile names based on opening percent.

Since factors other than opening percent can influence real-world wagering activity, we next add our controls. The results indicate a pattern similar to the preliminary model (see web appendix D for details on the race-specific and [horse] odds-specific intercepts). We again find a statistically significant negative effect on closing percent from phonetic score ($\beta_{\text{phonetic score}} = -2.69$, $z = -9.85$, $p < .001$) and a significant, positive effect from opening percent ($\beta_{\text{opening pct}} = .41$, $z = 3.79$, $p < .001$). Furthermore, we find a significant phonetic score × opening percent interaction ($\beta_{\text{phonetic score} \times \text{opening pct}} = .19$, $z = 5.10$, $p < .001$), suggesting differences in wagering activity based on phonetic score and opening percent.

To further explore this pattern of results, we graphically plot phonetic score and opening percent at their 5th and 95th percentiles and examine the magnitude of the effect on closing percent. We use spotlight analysis to examine the effect of high versus low phonetic score (e.g., phonetic score = –2.5 vs. phonetic score = 2) for risky versus safe prospects as indicated by opening percent. The results suggest that for risky prospects, people wager more on volatile names. As figure 1 depicts, at the 5th percentile of opening percent—that is, for a risky prospect—we find a significantly higher closing percent, indicating greater wagering on volatile compared to calm names. Specifically, for a risky prospect, closing percent is 10.41 points higher for a volatile versus calm name ($p < .001$). Conversely, when the probability of winning is higher—that is, for a safe prospect—bettors wager more on calm names. For example, a calm name predicts a 5.42 increase in closing percent versus a volatile name amid low prospect risk ($p = .055$).

Endogeneity Concerns. It could be argued that the owners naming the horses, or odds-makers establishing odds, could have used existing knowledge about the phonetic elements of a name to influence future wagering. However, the process of naming a horse includes numerous controls, beginning with the owning entity submitting the name for consideration well before the horse's first race. The owner does not determine the name independently; it must be in line with approved guidelines. Importantly, before a horse's first race, odds are set based on internal (e.g., horse lineage, jockey) and external (e.g., competing horses, race location) factors. After odds are established, bettors then place wagers, causing odds to fluctuate upward or downward. In subsequent races, the process is similar, with the horse's prior performance serving as a new informative factor in establishing odds for future races. Thus, the owner's actions in naming a horse do not directly affect the odds of winning, making endogeneity concerns less likely. The horse's name poses little risk in correlating with the error term predicting the dependent variable. Importantly, to address endogeneity concerns further, we conducted several studies in a controlled setting to test the proposed effect.

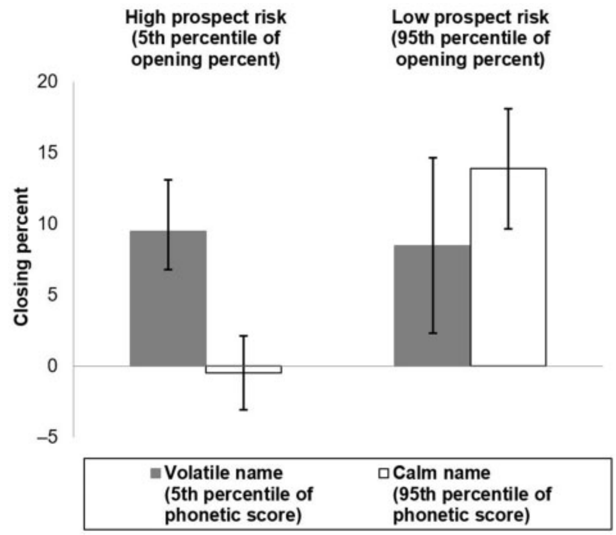
The results of this study provide evidence of our proposed effect (hypothesis 1) in the marketplace. We find that people prefer (wager more on) volatile names for risky prospects and prefer calm names for safe prospects.

STUDY 3: SIMULATED HORSE RACING

The main aim of study 3 was to test the proposed effect in a randomized, controlled setting to address limitations of study 2, such as endogeneity. Participants played a horse racing game in which horses of different names were shown with different probabilities of winning. Participants were asked to invest in the horse(s) that they thought would win the race. In order to address endogeneity, horse names were randomly matched with probabilities of winning; that is, *Sabercat* could appear with 2-to-1 odds for one participant and 10-to-1 odds for another participant. If our proposed effect emerges in such a randomized setting, then it makes the endogeneity concerns of study 2 less likely. A second aim of this study was to use names with different phonetic scores; we used 45 names with phonetic scores ranging from –3.0 to +2.5. Third, we used different levels of risk that we matched with horse names randomly; the risk levels ranged from a safe prospect of 2-to-1 to a risky prospect of 21-to-1. The aim of using names with different phonetic scores and matching with different risk levels was to test the robustness of the proposed effect. Finally, unlike later studies that used a between-participant design, in this study we used a within-participant design to test robustness of the effect; that is, all participants saw all levels of risk for an assortment of names (45 in total).

FIGURE 1

FOR HIGH- (LOW-) RISK BETS IN STUDY 2, EVIDENCE OF HIGHER EVALUATION FOR VOLATILE (CALM) NAMES



Procedure

Ninety-two students from a US university took part in an experiment for partial course credit. Participants were informed that they would be playing a game with the goal of earning as many points as possible. The more points they earned, the higher their chances of winning a $75 gift card. The game entailed predicting the winning horse (out of a total of nine horses) in five different horse races. Each race had nine horses, and each participant played five such races. For each of the five races, a participant was given exactly 100 points to allocate across any of the nine total horses. They could allocate all 100 points or 0 points to a horse, or some value in between to numerous horses.

After completing a practice round, participants invested in the five races sequentially. Each of the five races included a unique lineup of nine horses, which was randomly presented to participants with odds randomly assigned to each of the nine entrants. That is, each participant saw the same five races, but each race and the odds of each horse in that race were randomized. For example, participant 1 might see the horse *Sabercat* as the fifth of nine entries in race 3, while participant 2 might see this same horse in race 5 (still as the fifth of nine entries). Moreover, for participant 1, *Sabercat* might appear with 2-to-1 odds, while participant 2 might see this same horse with 15-to-1 odds.

Given our controlled study design—five races, each with nine horses—we randomly selected 45 names from the Kentucky Derby data (study 2). Names were normally distributed over phonetic score (through the Shapiro–Wilk test; $W = .98$, $p = .739$), and this set of names ranged from 3.0 to +2.5 in phonetic score ($M = .04$, $SD = 1.40$). We also randomly assigned values to the odds of winning similar to the distribution of odds within Kentucky Derby data, which fell in the range of 2-to-1 to 21-to-1 ($M = 11.4$, $SD = 5.8$).[4] The dependent variable of evaluation was captured by the points that participants allocated to a horse. The stated (given) odds of winning served as our predictor of whether risk was high or low, which we rescaled to a percentage (e.g., 9-to-1 odds = 10% chance of winning = 90% risk).

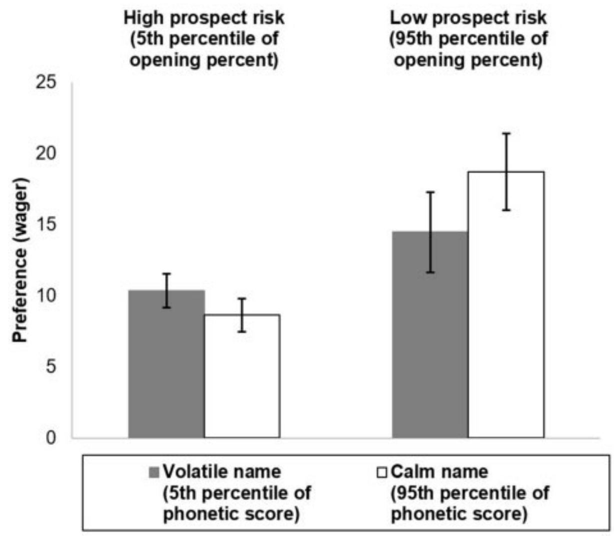
Results and Discussion

We used a hierarchical (multilevel) mixed-effects linear regression model to account for the nested structure of the data, as each participant (level 1) wagered on horses (level 2) within each race (level 3). We allowed units at each of these levels to have different intercepts. Our model predicted evaluation as a function of phonetic score, prospect risk, and their interaction. The results indicated significant main effects for phonetic score, prospect risk, and their interaction (see web appendix D for detail on the race-specific, horse-specific, and individual-specific intercepts). A one-unit increase in phonetic score resulted in a .66 reduction in preference for a horse ($\beta_{\text{phonetic score}} = -.66$, $z = -2.07$, $p = .039$), all else being equal. A one-unit increase in prospect risk resulted in a .25 decrease in evaluation ($\beta_{\text{prospect risk}} = -.25$, $z = 6.83$, $p < .001$).

Most relevant to our theorizing was a significant phonetic-score × prospect risk interaction ($\beta_{\text{phonetic-score} \times \text{prospect risk}} = -.05$, $z = -2.17$, $p = .030$). To understand the magnitude of the phonetic score × prospect risk interaction, we conducted a spotlight analysis at high and low (95th and 5th) percentiles. For a risky prospect (95th percentile of prospect risk), we found evidence of higher evaluation for horses with volatile names. Specifically, an individual's wager is 1.72 points higher for a volatile versus calm horse name ($p = .073$). Conversely, at the 5th percentile of prospect risk—that is, a safe prospect—participants wagered more on horses with calm names, with a calm name predicting a 4.24 increase in wagering relative to a volatile name ($p = .057$). Figure 2 illustrates this pattern, providing evidence in support of hypothesis 2.

FIGURE 2

STUDY 3 REVEALS SIMILAR PATTERN AS STUDY 2, WITH VOLATILE (CALM) NAMES PREFERRED AMID RISKY (SAFE) PROSPECTS



STUDY 4: EXAMINATION IN A NEGATIVE DOMAIN

In the studies thus far, the risky prospects had positive outcomes, such as winnings from a wager or the success of a product. Moreover, the decisions were voluntary and avoidable. In study 4, we examine a relatively unavoidable, negative risky event—landfall of a hurricane. We use data of 92 hurricanes that made landfall in the United States between 1950 and 2012 (adopted from Jung et al. 2014), with the number of fatalities serving as our dependent variable. Our rationale for using hurricanes was as follows: if our theorizing is correct, the pattern of results found in studies 2 and 3 should reverse in a negative domain. A risky prospect in a positive domain has a low chance of gain (e.g., 10% chance of winning), but a risky prospect in a

4 Phonetic score and the odds reflect a similar range to that in study 1. For example, in the real-world data, phonetic score ranged from –4 to +3 ($M = -.06$, $SD = 1.39$), and morning odds ranged from 2 to 29 ($M = 7.5$, $SD = 6.6$).

negative domain has a high chance of loss (e.g., 90% chance of losing).

We explain our predictions using two actual volatile and calm hurricane names (our data set contains 92 hurricane names): *Gustav* (phonetic score = –2.0; a volatile name) and *Carmen* (phonetic score = +3.0; i.e., a calm name). First, when the probability of the hurricane causing damage is high (e.g., a Category 5 hurricane—a risky prospect with imminent loss), people are likely to be more worried about how severe the damage might be. A hurricane with a volatile name such as *Gustav* should result in a wider probability band than a calm name such as *Carmen*. Therefore, the likelihood of loss should appear higher with *Gustav*. One downstream influence of perceptions of severity would be that people are more likely to comply and take more precautions with the volatile name, resulting in fewer lives lost. In the case of a calm name, because of a narrower probability band, people might perceive the storm as less of a threat and thus take fewer precautions, resulting in the downstream effect of more lives lost (relative to a volatile name).

Second, when considering hurricanes that are less likely to cause damage (e.g., a Category 1 storm—a safer prospect), people might weigh the cost of evacuation against the cost of staying. As the hurricane is not of the highest category, they may not evacuate without the need to do so (i.e., taking expensive precautions when it is not necessary). At this point, because of the wider probability band, the hurricane with a volatile name should appear less likely to cause harm. Therefore, we would expect less compliance and greater fatalities for a Category 1 hurricane with a volatile name than with a calm name.

Finally, Jung et al. (2014) find in their research that hurricanes whose names were categorized as female were more likely to cause damage compared to hurricanes with male names. We, therefore, control for the gender of the hurricane name to see whether our proposed effect still emerges.

Procedure

We used an existing archival data set that measured select variables related to the number of fatalities attributed to hurricanes in the United States between 1950 and 2012 (Jung et al. 2014). The data provided Atlantic tropical storm names as issued by the National Oceanic and Atmospheric Administration's National Hurricane Center and consisted of information about 92 hurricanes. We first calculated the phonetic score of the hurricane names. Similar to study 2, the naming procedure included numerous controls. First, names of hurricanes are predetermined; that is, they are not decided at the last minute depending on the expected severity of the hurricane. Second, the names follow the strict naming procedures set by the World Meteorological Organization (WMO); six lists of 21 names are used in rotation and recycled every six years. For each of the six lists, names progress alphabetically (excluding names beginning with Q, U, X, Y, and Z) and rotate between names that are predominantly male to predominantly female (e.g., 2021's list progresses from Ana to Bill to Claudette). The only time a change occurs is when the WMO deems that casualties or damages from a prior storm warrant a name change (e.g., as was the case with Hurricane Katrina in 2005). Third, all names are designed with the same intent of aiding in the relay of storm information; thus, names are designed to be short, yet still distinctive from one another.

The data set categorized hurricanes on a 1 to 5 scale as defined by the National Hurricane Center. For example, the center defines Category 3 and above as "major" in that these can result in significant loss of life and damage, while it describes Categories 1 and 2 as more "preventive" in nature. The dependent variable was the number of fatalities attributed to a given hurricane. We used a zero-inflated Poisson regression because of the presence of zeros and overdispersion in the dependent variable.[5] In our model, we predict the number of fatalities as a function of the hurricane's name (phonetic score), the category/severity of the hurricane (category), the gender of the hurricane name, and the interaction of these variables. Moreover, as this Poisson distribution was complemented by a binary model determining whether or not a death occurred, we used the storm's category/severity (category) as the predictor. Thus, this model allows for different sets of independent variables to jointly predict the binary (whether or not a death occurred) and count (number of fatalities) parts of the model.

Results and Discussion

The results revealed a significant main effect for name ($\beta_{\text{phonetic score}} = –.77$, $z(85) = –5.61$, $p < .001$) such that increased phonetic scores resulted in fewer deaths. For the storm's category and gender, we found significant main effects suggesting greater fatalities from more severe storms ($\beta_{\text{category}} = .43$, $z(85) = 10.51$, $p < .001$) and from storms with female names ($\beta_{\text{gender}} = 1.73$, $z(85) = 11.94$, $p < .001$). The model revealed significant interaction effects for all variables: phonetic score × category ($\beta_{\text{phonetic-score} \times \text{category}} = .14$, $z(85) = 2.62$, $p < .01$), phonetic score × gender ($\beta_{\text{phonetic-score} \times \text{gender}} = –.98$, $z(85) = –6.52$, $p < .001$), category × gender ($\beta_{\text{category} \times \text{gender}} = –.57$, $z(85) = –10.37$, $p < .001$), and the three-way interaction ($\beta_{\text{phonetic-score} \times \text{category} \times \text{gender}} = .48$, $z(85) = 8.13$, $p < .001$). Also, in predicting the binary outcome of the model (i.e., whether or not a death occurred), the coefficient for category suggests a decrease in the log odds of an inflated zero as storm category increases ($\beta_{\text{category(inflate)}} =$

5 The Vuong model (Greene 1994; Vuong 1989) validated our choice of zero-inflated Poisson over standard Poisson ($z = 1.81$, $p = .035$). Moreover, we ran the model using a robust standard error calculation.

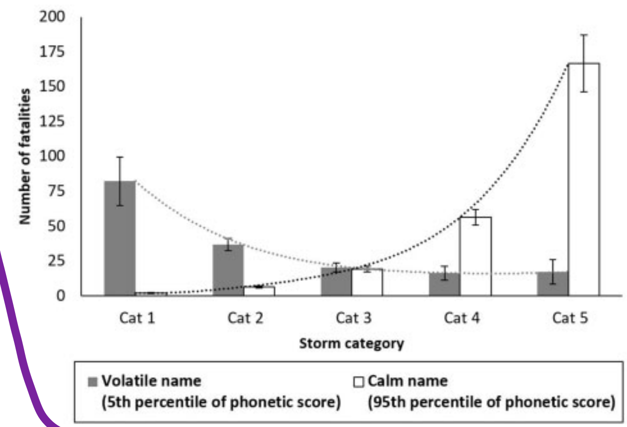
95th percentile of only 92 hurricanes is like 4-5 names

–.76, $z(85) = –1.79$, $p = .074$), albeit at marginal significance. In other words, the presence of zero fatalities is more likely to result from less (vs. more) severe storms.

As in the prior studies, we conducted a spotlight analysis at the 5th and 95th percentiles of high and low phonetic score hurricane names (–1.5 and +2.0) and examined this over storm severity (Category 1–5 storms). Figure 3 graphically presents these findings. For lower (i.e., less severe) storm categories, we found evidence of fewer fatalities for calm names versus volatile names (Cat 1 $\text{fatalities}_{\text{calm minus volatile name}} = –80.19$, $z(85) = –9.05$, $p < .001$; Cat 2 $\text{fatalities}_{\text{calm minus volatile name}} = –30.23$, $z(85) = –2.33$, $p < .001$). We found no effect within Category 3 hurricanes (Cat 3 $\text{fatalities}_{\text{calm minus volatile name}} = –1.23$, $z(85) = –.64$, $p = .525$). For more severe hurricanes where probability of harm is higher (i.e., Category 4 and 5 storms), we found significantly fewer fatalities for volatile names (Cat 4 $\text{fatalities}_{\text{calm minus volatile name}} = 40.17$, $z(85) = 4.25$, $p < .001$; Cat 5 $\text{fatalities}_{\text{calm minus volatile name}} = 149.59$, $z(85) = 12.35$, $p < .001$). Therefore, the results indicate that the perception of volatility reverses evaluations in a negative domain. We next present studies 5, 6, and 7, which test for the theoretical mechanism.

FIGURE 3

IN NEGATIVE DOMAIN (STUDY 4), EVIDENCE OF GREATER PRECAUTIONS FOR VOLATILE (CALM) NAMES AMID HIGH (LOW) SEVERITY



STUDY 5: PROBABILITY BAND AND PERCEIVED VOLATILITY

The main aim of study 5 was to test hypothesis 2: for a given prospect risk, volatile (calm) names would make the probability band appear wider (narrower). We posit that the volatility evoked by the name results in more perceived fluctuations from the given risk levels for that prospect. Therefore, regardless of the given risk level, a volatile prospect name would result in a wider probability band, whereas a calm prospect name would result in a narrower probability band. Additionally, we used different prospect risk levels to add to the findings of study 3.

Study 5 also tested for an alternate account based on the match between name and prospect. This account would argue that risky names are preferred for risky prospects, while calm names are preferred for safe prospects. The matching account relies on the fit or alignment between two entities that causes higher evaluation. The matching account applied to our context would predict a difference in evaluation but no change in the probability band around the given risk level. However, our proposed account predicts that the evoked volatility due to the phonetic elements of the name would widen the probability band for a volatile prospect name compared to a calm name. In sum, if our proposed account is true, then the probability band around the same risk level would appear wider with a volatile name compared to a calm name. However, if the matching account is true, then the probability band would stay the same irrespective of the name.

Procedure

Two hundred ten US participants ($M_{age} = 33.3$, 64% male) were recruited from MTurk in return for compensation. Participants read about a product that performs radon testing, the consequences of undetected radioactive radon gas in homes, and the importance of having a test that can detect its presence. The description noted that some new products, along with measuring current levels of radon, can also provide accurate forecasts of future long-term radon levels as an added consumer safeguard. Subsequently, participants were presented with a description of a radon testing product that included the brand name and information about the product's anticipated effectiveness (e.g., "75% effective at accurately forecasting future radon levels"). Participants were randomly presented with a brand name that was either high or low in phonetic score; names were based on a normally distributed list of over 50 names, with phonetic score ranging from –4.0 to +4.0 ($M = .20$, SD = 2.6).[6]

The brand was presented as being effective at a high (75%), medium (51%), or low (25%) level of accuracy in forecasting future radon levels. That is, high level of forecasting accuracy was a safe prospect, while a low level of forecasting accuracy was a risky prospect. Our dependent variable was the width of probability band perceived around the given risk level. In order to find out the probability band, we asked participants to enter their upper- and lower-bound estimates of how effective they thought the brand would be in forecasting future radon levels. The

6 As previously noted, brand names were selected from actual USPTO (i.e., trademark) submissions (www.uspto.org).

difference between the upper and lower values was used as the width of the probability band; this dependent measure of probability band was regressed on phonetic score while controlling for prospect risk.

Results and Discussion

The analysis yielded a significant main effect for phonetic score ($F(3, 206) = 4.09$, $p = .044$, $\eta_p^2 = .019$). There was no significant effect for prospect risk ($F(3, 206) = .83$, $p = .438$). These findings suggest a wider probability band for volatile names. Specifically, a one-unit decrease in phonetic score—that is, a more volatile name—predicts a 1.05 widening of the probability band ($\beta = 1.05$, $t(206) = 2.02$, $p = .044$).

In sum, the findings of this study support hypothesis 2 in that volatile prospect names result in a wider probability band, but calm prospect names result in a narrower probability band. The findings ruled out the matching account, which would predict no difference in the width of the probability band, and also found support for our proposed account that the evoked volatility from the phonetic elements of a name change the probability band around the given risk level.

STUDY 6: INFLUENCE OF NAMES ON EVALUATION, MEDIATED BY PROBABILITY BAND

The aim of study 6 was to test the theoretical account through a mediating process. A volatile name is believed to evoke the psychological attribute of volatility (as demonstrated in study 1), which would widen the probability band of a given risk level (as demonstrated in study 5), which in turn should influence evaluation. Therefore, we examine whether the influence of a name's phonetic score on evaluation—moderated by prospect risk—is mediated by the probability band. In study 6, we explored this effect at high and low prospect risk (e.g., 25% and 75% chance of success) and varied whether the name was volatile or calm via the phonetic score. To rule out potential demand effects, we counterbalanced elicitation of probability band and evaluation.

Procedure

One hundred seventy-nine MTurk participants ($M_{age} = 36.62$, 54% male) took part in this study for monetary compensation. Participants were instructed that they would be providing evaluations for one or more branded products. They then read about a new pharmaceutical product, including its name, chance of success, and claimed benefits and risks. Participants were randomly assigned a brand name from a normally distributed set of 34 USPTO names with a phonetic score ranging from –4.0 to +4.0 ($M = -.04$, $SD = 1.87$). This brand name appeared with the product's reported benefits (of enhanced memory and recall) and risks (of restlessness or anxiousness) in clinical trial testing. Participants were also randomly assigned to a risky or safe prospect condition—that is, 25% (risky) and 75% (safe) success in clinical trials, respectively. Measurement of probability band and evaluation were counterbalanced between participants; that is, the order of elicitation was randomized: (i) participants were asked to enter their upper- and lower-bound estimates of how successful they thought the brand would be in delivering the expected benefits, with the difference between these two values representing the width of the probability band; and, (ii) participants indicated how much value they saw in the brand on a seven-point scale (1 = Extremely low value, 7 = Extremely high value), serving as our dependent variable of evaluation. Phonetic score was calculated as in prior studies such that positive (negative) values indicate calm (volatile) names.

Following Hayes (2015), our model tested the moderating influence of prospect risk (W) on the indirect effect of phonetic score (X) on evaluation (Y) through the probability band (M); specifically, $M = i_M + aX + e_M$ and $Y = i_Y + c'X + b_1M + b_2W + b_3M\,W + b_4X\,W + e_Y$. We examined the indirect effect of probability band, conditional on prospect risk: following Hayes (2015), this is the product of the effect of phonetic score on probability band and the effect of probability band on evaluation, conditional on prospect risk. Represented as $\omega = a\,b_1 + a\,b_3W$, this can be interpreted as a linear function of prospect risk (W) with intercept $a\,b_1$ and slope $a\,b_3$, the latter of which is the index of moderated mediation (i.e., $a\,b_3$). Applied to our model, this measured the effect of prospect risk on the indirect effect of phonetic score on evaluation through probability band. We use the above notations in our results section.

Results and Discussion

The analysis revealed the following effect of volatile versus calm names on probability band: a volatile (calm) name resulted in a wider (narrower) probability band such that a one-unit increase in phonetic score resulted in a 1.9 decrease in probability band ($a = -1.53$, 95% CI [–2.91,–.16], $p = .029$, $\eta_p^2 = .027$). For the model predicting evaluation, the main effect of probability band was not significant ($b_2 = .11$, 95% CI [–.06, .28], $p = .213$). A significant probability band × prospect risk interaction ($b_3 = .45$, 95% CI [.11, .78], $p = .010$, $\eta_p^2 = .038$) suggests that the effect of probability band on one's evaluation is dependent upon the level of prospect risk. Based on these findings, the negative slope of the indirect effect ($ab_3 = -1.53 \times .45 = -.69$) suggests that the indirect influence of a volatile (calm) name on evaluation through probability band is an increasing (decreasing) function of prospect risk. As

TABLE 1

STUDY 6 REGRESSION COEFFICIENTS WITH CONFIDENCE INTERVALS

	Probability band (M)				Evaluation (Y)[+]			
		Coefficient	95% CI			Coefficient	95% CI	
Phonetic score (X)	$a \rightarrow$	−1.53*	−2.91	−.16	$c' \rightarrow$	.72	−.81	2.24
Probability band (M)					$b_1 \rightarrow$	.11	−.06	.28
Prospect Risk (W)					$b_2 \rightarrow$	−29.88**	−43.57	−16.19
$M \times W$					$b_3 \rightarrow$	.45**	.11	.78
$X \times W$					$b_4 \rightarrow$	−3.38*	−6.42	−.33
Constant	$i_M \rightarrow$	34.89**	32.33	37.46	$i_Y \rightarrow$	64.10**	57.25	70.94
		$R^2 = .03$				$R^2 = .20$		
		$F(1, 177) = 4.87, p = .029$				$F(5, 173) = 8.72, p < .001$		

[+]For ease of interpretation, evaluation is rescaled (0 to 100) to match that of probability band.
*$p < .05$. **$p < .01$.

described by Hayes (2017), the significance of the weight of this indirect effect—that is, the index of moderated mediation—is best examined via bootstrap confidence interval.

The analysis using a bootstrap technique for indirect effects (5,000 bootstrap repetitions) revealed a 95% confidence interval not containing zero. Specifically, for each one-unit increase in phonetic score, the index of moderated mediation was –.68 (95% CI [–1.61, –.01]). The results are summarized in table 1 and indicate the following: a volatile (calm) name makes the probability band appear as wider (narrower). The width of the probability band mediates the influence of phonetic score on evaluation, conditional on prospect risk. The ensuing pattern is that a volatile (calm) name widens (narrows) the probability band, resulting in increased evaluation amid high (low) prospect risk.

STUDY 7: MANIPULATING VOLATILITY ORTHOGONALLY

The main aim of study 7 was to provide further evidence for the role of perceived volatility evoked by the phonetic elements of a name in causing our proposed effect. In order to do so, we manipulated volatility orthogonally. We randomly assigned participants to one of two conditions: when volatility is made more accessible versus when calmness is made more accessible. We predicted that for those whom the construct of volatility was made more accessible, a risky prospect with a volatile name would be evaluated higher; this is similar to the pattern we have witnessed thus far. However, the evaluation of a safe prospect with a calm name would diminish because the orthogonal manipulation of volatility should counteract the calmness evoked by the name. For those whom the construct of calmness was activated, this pattern should reverse. We should find greater evaluation for the calm name with the safe prospect, consistent with our prior results. However, evaluation for the volatile name should diminish with the risky prospect (as compared to a calm name) because the calmness from the manipulation would counteract the volatility evoked by the prospect's name. The design of the study was a 2 (name: volatile vs. calm) × 2 (prospect: safe vs. risky) × 2 (construct accessibility: volatility vs. calmness) between-participants design.

We used study 1's visuals to make volatility or calmness more accessible. Before using these visuals, we pretested for whether the volatile (calm) images succeeded in making the construct of volatility (calmness) more accessible. We also measured mood (i.e., positive and negative affect), as one could argue that volatile (calm) images can activate a bad (good) mood.

Pretest

One hundred fourteen US participants ($M_{age} = 34.80$, 57% male) were recruited from MTurk in return for compensation and were randomly assigned to see either the volatile or calm visuals. Those assigned to the volatile (or calm) condition saw the same seven volatile (or calm) visuals as in study 1, which appear in web appendix C. After seeing all seven visuals, participants took part in a word/nonword recognition task. Words appeared one at a time on the computer screen, and participants were asked to press Q if it was a nonword and P if it was a word, as quickly as possible. The computer recorded the response time between presenting the stimulus and registering a response. Each participant was randomly shown six volatile words (risky, volatile, inconsistent, erratic, unreliable, uncertain), six calm words (stable, calm, safe, consistent, reliable, constant), and six nonwords (conudrick, cota, helempki, bashitig, donkangh, valcuni; Mishra 2009). It was expected that volatility would be rendered more accessible for participants who had seen the volatile images, whereas the concept of calmness would be made more accessible for participants who had seen the calm images. Participants concluded the study by responding to the 20-

item positive and negative affect scale (PANAS; Watson, Clark, and Tellegen 1988).

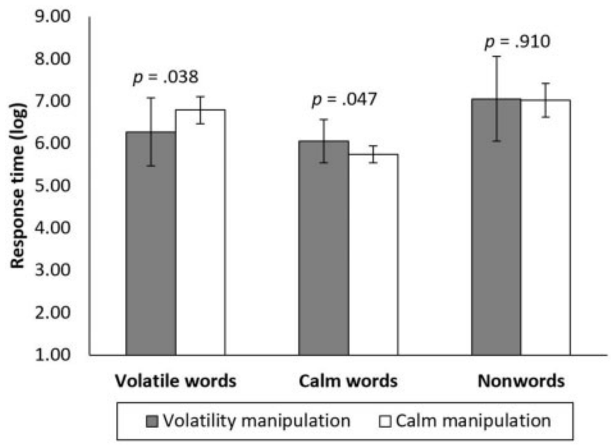
Logarithmically transformed response times were averaged across volatile words, calm words, and nonwords, which (as a measure of accessibility) were subsequently subjected to a MANOVA. Analysis yielded a significant manipulation × accessibility interaction ($F(3, 110) = 3.22$, $p = .026$, $\eta_p^2 = .081$). A decomposition of this interaction across accessibility revealed that (i) for volatile words, participants shown the volatile images responded faster ($M = 531$ milliseconds) than participants shown the calm images ($M = 890$ milliseconds, $F(1, 112) = 4.43$, $p = .038$); (ii) for calm words, participants shown the calm images responded faster ($M = 313$ milliseconds) than participants shown the volatile images ($M = 427$ milliseconds, $F(1, 112) = 4.04$, $p = .047$); and (iii) for nonwords, no significant difference emerged across participants shown the volatile or calm images ($M = 1{,}161$ milliseconds vs. 1,121 milliseconds, $F(1, 112) = .01$, $p = .910$). Figure 4 graphs these findings, reported with the log-transformed response times from the MANOVA. Finally, to test the alternate account that the volatile or calm visuals had a differential effect on positive or negative affect, we ran a MANOVA that predicted positive and negative affect as a function of our volatility manipulation (high vs. low). The model indicated no effect ($F(2, 111) = .04$, $p = .965$) on positive affect ($p = .821$) or negative affect ($p = .770$), thus ruling out the mood account.

Main Study Procedure

Four hundred fourteen MTurk participants ($M_{age} = 37.26$, 57% male) took part in return for monetary compensation. Participants were randomly assigned to one of the eight between-participant conditions per our 2 (name: volatile vs. calm) × 2 (prospect: safe vs. risky) × 2 (construct accessibility: volatility vs. calmness) study design. First, participants were instructed that they would be shown names of products and asked to provide their judgments and perceptions. Similar to study 1, they were instructed to read the brand name carefully, and to repeat it to themselves a few times. Participants were then informed that before beginning the main part of the survey, they would be taking part in another study involving pictures or visuals that they may be asked about later in the survey. The seven stimuli (volatile or calm images) were then presented. Ostensibly, upon returning to the main part of the survey, participants read about a new pharmaceutical product in a format similar to study 6. Those in the calm (volatile) name condition saw one of four names with a phonetic score ranging from +3.0 to +4.0 (–3.0 to –4.0), and those assigned to see the high (low) chance of success read about benefits occurring in 75% (25%) of clinical trials. After reading this scenario, participants indicated how much value they saw in the brand on a seven-point scale

FIGURE 4

STUDY 7 PRETEST SUGGESTS GREATER ACCESSIBILITY OF VOLATILITY (CALMNESS) WITHIN VOLATILE (CALM) MANIPULATION



(1 = Extremely low value; 7 = Extremely high value), serving as our dependent variable of evaluation.

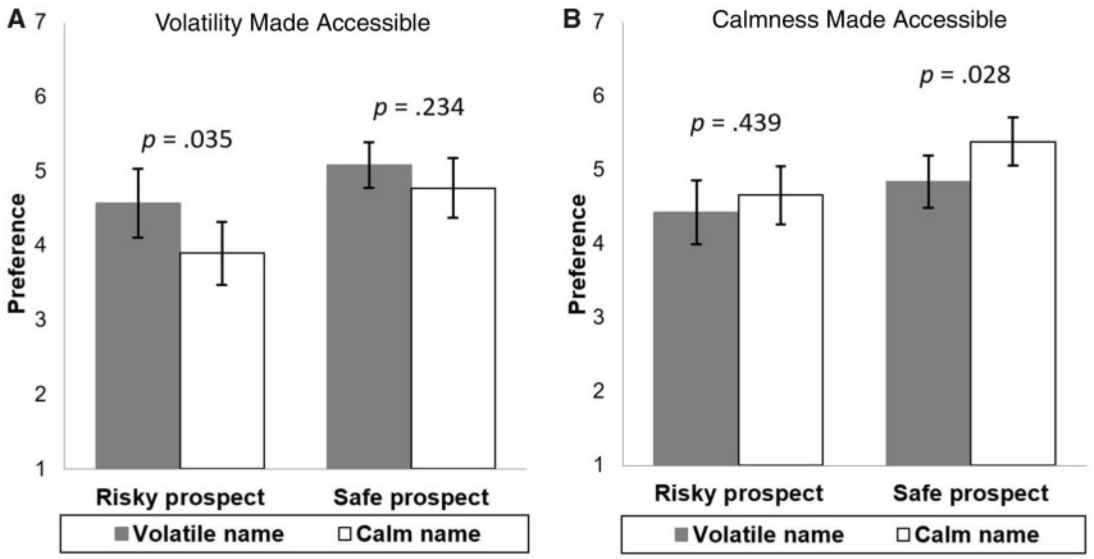
Results and Discussion

Regressing evaluation on variables of name (volatile vs. calm), prospect (safe vs. risky), construct accessibility (volatility vs. calmness), and their interaction revealed a significant effect ($F(7, 406) = 5.31$, $p < .001$). Significant main effects emerged for name ($F(1, 406) = 4.87$, $p = .028$, $\eta_p^2 = .003$), prospect ($F(1, 406) = 7.75$, $p = .006$, $\eta_p^2 = .046$), and construct accessibility ($F(1, 406) = 5.23$, $p = .023$, $\eta_p^2 = .007$), with a significant three-way interaction ($F(4, 406) = 2.95$, $p = .020$, $\eta_p^2 = .027$). Decomposing the three-way interaction, we examined the interaction of name × prospect when volatility versus calmness was made accessible. When volatility was made more accessible, participants evaluated the risky prospect with a volatile name higher than with a calm name ($\text{Evaluation}_{\text{risky prospect: volatile vs. calm name}} = .68$, $t(406) = 2.12$, $p = .035$). However, there was no significant difference in evaluation when a safe prospect appeared with a volatile or calm name ($\text{Evaluation}_{\text{risky prospect: volatile vs. calm name}} = .31$, $t(406) = 1.19$, $p = .234$) (see panel A of figure 5). Such a pattern is consistent with our prediction that making volatility accessible affects evaluation of risky prospects, but diminishes the effect for calm (vs. volatile) names amid safe prospects.

When calmness was made more accessible, participants evaluated a safe prospect with a calm name higher than with a volatile name ($\text{Evaluation}_{\text{safe prospect: calm vs. volatile name}} = .54$, $t(406) = 2.21$, $p = .028$). Within a risky

FIGURE 5

MAKING VOLATILITY OR CALMNESS ACCESSIBLE MODERATES THE PROPOSED EFFECT



prospect, this effect was diminished ($\text{Evaluation}_{\text{safe prospect: calm vs. volatile name}}$ = .23, $t(406)$ = .77, p = .439). Thus, in making calmness more accessible, we find the expected pattern of evaluation amid a safe prospect, and we find an attenuation of this effect amid a risky prospect. This is exhibited in panel B of figure 5. Therefore, in study 7, we find support for our volatility-based account by manipulating volatility orthogonally.

GENERAL DISCUSSION

In this research, we find that people prefer names with a low phonetic score for risky prospects, but for safe prospects they prefer names with a high phonetic score (hypothesis 1). We attribute this to volatile (calm) names evoking the psychological attribute of volatility (calmness). Moreover, such evoked volatility makes the probability band appear wider (narrower) for a volatile (calm) name, all else equal. Study 1 used a four-stage procedure to demonstrate how phonetic score affects volatility. In study 2, we used real-world data from the Kentucky Derby and found evidence of greater wagering on horses with volatile names when they were risky prospects. Conversely, for safe prospects, we found evidence of greater wagering on horses with calm names. Study 3 replicated the findings of study 2 in a controlled setting. Study 4 used hurricane data to show that—in the negative domain—fewer fatalities occurred when a severe storm had a volatile name (while controlling for gender of the name). Study 5 demonstrated that a volatile (calm) name resulted in a wider (narrower) probability band. Study 6 used a moderated mediation design to demonstrate the influence of calm versus volatile names on the evaluation of risky and safe prospects, indirectly through the probability band. In study 7, we manipulated volatility orthogonally and showed a moderation of the proposed effect.

Theoretical Implications

Our findings contribute to the larger theoretical area of phonetic symbolism, which has demonstrated a substantial influence on one's perceptions and preferences based on a single change to the phonetic element of a word. Our first theoretical contribution is that we examine the impact of the name in totality on risk assessment rather than of only one phonetic element (e.g., *floog* vs. *fleeg*). This allows us to consider how all of the phonetic elements within a name, together, can evoke different psychological attributes. In the marketplace, numerous names and brands exist that differ on not just one, but many, phonetic elements (e.g., Walmart vs. Target). A name can have numerous phonetic elements, and they are experienced in totality rather than separately. Our work allows predictions about people's evaluations by simultaneously taking into account many phonetic elements.

Second, our work provides a deeper understanding of the process when a particular psychological attribute (in our work, volatility) is evoked by the phonetic elements. We demonstrate that the phonetic elements of a name can influence evaluation by changing perceived risk estimates. The probability band around the same risk level appears wider when associated with a name that evokes volatility. Third, we contribute to the literature on decisions involving risky prospects. In the real world, many prospects with various degrees of risk have a name associated with them, such as stocks and brands. Our work provides a new insight into understanding people's evaluations by taking into account the phonetic elements of a risky prospect's name.

Practical Implications

This research provides guidance for practitioners trying to maximize evaluation for a given product, service, or policy. Just as meaningless attributes can influence brand preference (Carpenter, Glazer, and Nakamoto 1994), the volatility or calmness of a name may allow brands to differentiate on what may appear to be a meaningful point of difference for a product (e.g., a more or less volatile perception). For decisions involving greater risk and reward for the consumer, marketing decision-makers may benefit from using more volatile names. That is, a risky financial portfolio targeting adventurous investors that seek high risk and reward could use a volatile name. Conversely, when people seek more certain outcomes, a calm name could be more effective; for example, a conservative money market account may be perceived as more stable and thus more effective in garnering interest from cautious investors if its name appears calm. Or, consider a charity or fundraising initiative with a high or low probability of success at its onset. In this instance, a more volatile project name could garner greater donations when positioned as an underdog or long shot. Conversely, when positioned as having a high chance of success, the project could receive greater buy-in when its project name is calmer. In sum, the findings of this research give cues to decision-makers in areas such as message development, forecasting of choice, and evaluation of a given product, service, or policy.

Limitations and Future Research Directions

Past research has documented many factors that influence people's evaluations of risky prospects in the real world. If we consider real-world evaluations such as betting in a horse race or assessing risk of hurricanes, several extraneous factors work in conjunction to affect risk assessment. We are not claiming that other factors will not affect people's evaluations. Instead, from a nomological network perspective (Cronbach and Meehl 1955), we are focusing on one specific antecedent—the phonetic elements of a risky prospect's name.

Second, we have demonstrated that volatility is one construct that is evoked because of the phonetic elements of a name, and we test for it via a mediation and moderation approach. It would be worthwhile for future research to consider other attributes that are evoked because of the phonetic elements that can affect evaluations. In our research, we consider evaluation of risky prospects as a function of the prospect's name and risk level. While we do not find evidence of boundary conditions or reversals in our proposed effect with regard to extreme levels of prospect risk, we do not directly examine the role of such factors as anxiety. Future research could seek to directly examine this. Moreover, one's chronic risk tolerance can also moderate the proposed effect. Future research can also examine how names might holistically impact judgments. For instance, would perceptions of long-term reliability or quality of a product be affected by the phonetic score of the brand name? Would a volatile or calm brand name be able to better recover from a service failure, or increase consumer evaluation of augmented product offerings (e.g., extended warranties, supplemental services).

Finally, specific to brand names, would an established brand be less susceptible to the effects of having a volatile versus calm name? Related to this, research on the moderating role of reputation (equity) of an existing brand could examine how the sound of a name might affect long-term brand health relative to its competitors.

DATA COLLECTION INFORMATION

The Derby data (Study 2) was from Churchill Downs' past performance race data from twinspires.com and drf.com. The hurricane names data for study 5 was obtained from the work of Jung et. al. (2014). Stages 1, 3 and 4 of study 1 (Q4 2018 and Q1 2019) and study 3 (Q1 of 2015) included participants from the University of Utah participant pool. Stage 2 of study 1 included participants from Amazon Mechanical Turk (MTurk). The Kentucky Derby data used in study 2 was purchased by the first author in Q4 of 2014 and Q1 of 2015. Studies 5, 6 and 7 were conducted on MTurk in Q1 2019. The data for all of the studies was collected and analyzed by the first author, except for stage 2 of study 1, which was collected by the second and third authors.

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