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From Karen to Katie: Using Baby Names to Understand Cultural Evolution

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Abstract

How do psychological processes shape how culture evolves? We investigated how a cultural item's popularity is shaped by the recent popularity of other items with features in common. Specifically, using more than 100 years of first-names data, we examined how a name's popularity is influenced by the popularity of that name's component phonemes in *other* names in the previous year. Building on mere-exposure research, we found that names are more likely to become popular when similar names have been popular recently. These effects are nonlinear, however, and overpopularity hurts adoption. In addition, these effects vary with phoneme position. We demonstrate the causal impact of similarity on cultural success in a natural experiment using hurricane names. An exogenous shock to a phoneme's frequency, due to the presence of the phoneme in the names of prominent hurricanes, boosts the popularity of names that share that phoneme. Taken together, our results suggest how the similarity between cultural items affects how popular they become and how culture evolves more broadly.

Keywords

social influences, naming

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Is it possible to predict which summer movies will be hits? Which political ideologies will catch on? Whether *Madison* or *Margaret* will be a more popular baby name next year?

Academics, popular-press writers, and practitioners alike have long been interested in trying to predict cultural evolution, or which cultural tastes and practices will become popular next (Gladwell, 2006; Simonton, 1980). Some ideas, styles, norms, and social movements catch on, while others languish. But predicting what will be popular in the future is notoriously difficult. Cultural evolution often seems random (Hahn & Bentley, 2003; Salganik, Dodds, & Watts, 2006), and even domain experts have great difficulty forecasting future success (Bielby & Bielby, 1994; Hirsch, 1972).

But might it be possible to predict how culture evolves? Might there actually be some regularity in the way culture changes over time (Lieberman, Michel, Jackson, Tang, & Nowak, 2007)? Most models of diffusion look at only a single cultural item (Bass, 1969; Rogers, 1995). In such models, the popularity of one technological innovation or style is neither facilitated nor inhibited by the popularity of other innovations or styles.

In contrast, we suggest that interitem similarity shapes cultural evolution. Just as culture influences psychological processes (Markus & Kitayama, 1991), the converse is also true: Psychological processes shape the norms, tastes, and choices that make up culture (Berger & Heath, 2005, 2008; Berger & Milkman, 2012; Heath, Bell, & Sternberg, 2001; Kashima, 2008; Schaller & Crandall, 2004). In particular, research finds that exposure to a stimulus increases preference not only for that stimulus, but also for related stimuli that have features in common with it (e.g., nonidentical but similar-looking shapes; Gordon & Holyoak, 1983; Landwehr, Labroo, & Herrmann, 2011; Monahan, Murphy, & Zajonc, 2000). Taken to the collective level, this suggests that the cultural success of a given item may be influenced by the popularity of similar items. Songs, for example, may be more likely to become popular if their chord progressions are similar to those in recent hits (Simonton, 1980).

To study this phenomenon quantitatively, we examined the popularity of first names given to babies born in the United States from 1882 to 2006. Words are composed of phonemes, or perceptually distinct units of sound (e.g., the name *Karen* consists of the sequence /kærən/). We examined whether a name's popularity (i.e., the number of babies given that name

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in a given year) is influenced not only by its own past popularity (i.e., same-item effects), but also by the popularity, in the previous year, of *other* names that include its component phonemes (i.e., cross-item effects). For example, we investigated whether the popularity of the name *Karen* is influenced by the recent popularity of other names that start with a hard *k* sound (e.g., *Carl* and *Katie*) or end with an *n* sound (e.g., *Darren* and *Warren*). We also examined whether any such influence varies depending on whether the phoneme in question appears at the beginning, middle, or end of the name.

We focused on names for a number of reasons. First, in many domains, producers determine the available options. Consequently, any patterns in observed similarity over time could merely be a result of production incentives. Movie studios or car manufacturers might make new products similar to old products because it allows them to retain the same personnel or production line. In contrast, choices of baby names are driven by individuals and are essentially unconstrained (i.e., parents can select any name they like). Thus, naming is an ideal domain for studying internal drivers of cultural evolution. Second, commercial efforts and advertising have relatively little influence on parents' name choices. Third, in naming, unlike in technology domains, there is little (if any) difference in quality between items, and one item does not have an obvious advantage over another (Gureckis & Goldstone, 2009; Lieberson, 2000). The absence of these factors makes it easier to examine how cross-item similarity influences cultural success.

Study 1: 280 Million Births

In Study 1, we used a hierarchical Bayesian model to estimate the impact of interitem similarity on name popularity. We acquired U.S. Social Security Administration data on the names given to babies born from 1882 to 2006 (more than 7,000 names and 280 million births). Controlling for the number of babies given each name in the previous year, the model estimated how the usage of a name in a given year was affected by the usage of its first, last, and middle phonemes in other names the previous year.

Preliminary results and model building

Figure 1 shows that the more phonemes a pair of names have in common, the more their popularities are correlated over time ($p < .01$). For a more rigorous examination, we used a formal statistical model that controlled for a name's direct effect on its own popularity, isolating cross-item effects on name popularity. To accommodate both the count nature of the data and the large number of zeros due to names being introduced and then dying off (i.e., being unused), we constructed what is commonly known as a spike-at-zero model (Morrison & Schmittlein, 1988), which contained two stages. As shown in Figure 2, Stage 1 modeled whether a given name (i) had the potential to be used (i.e., whether it was an "active" name) in

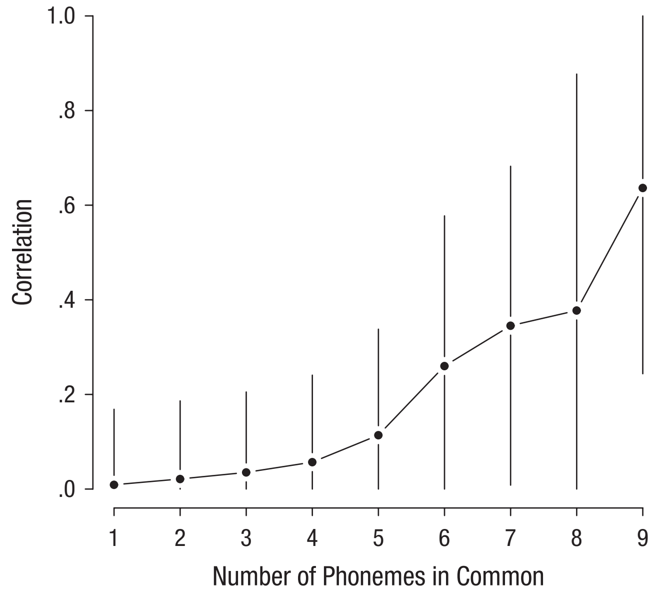

Fig. 1. Average correlation between the popularity of pairs of names over time as a function of the number of phonemes they have in common. Error bars show 95% confidence intervals.

year t. This latent indicator (Y_{it}) was equal to 1 if the name was potentially used and 0 otherwise. If the name was active (i.e., if $Y_{it} = 1$), usage was determined by a hierarchical Poisson regression model (Stage 2). If not, then usage was zero.

We relied on four sets of variables to estimate what drives the time-varying probability of name usage (potential activity), p_{it}, and, given potential usage, the average usage intensity (the Poisson mean, μ_{it}). The first set estimated two control effects. A baseline name effect accounted for the fact that some names are inherently more popular than others (e.g., across years, *Michael* may be more popular than *Max*). Thus, we included α_{pi} and α_{Ui} in the two-stage model to represent name i's impact on its probability of being active (p) and, conditional on its being active, its usage (U), respectively. A time effect was also included to account for the fact that there are more babies born in some years than others. Thus, we included δ_{pt} and δ_{Ut} to represent effects for the probability of names being active, and given activity, how frequently they are used in year t. The second set of variables consisted of a further control: the popularity of name i in the previous year, $t - 1$ (i.e., same-item effect). We included this variable in both stages of the model because we were interested in understanding the impact of phonetic similarity on a name's popularity after controlling for the name's own previous popularity. These effects are denoted as $\beta_{p1} * N_{i,t-1}$ and $\beta_{U1} * N_{i,t-1}$, where $N_{i,t-1}$ is the name's usage in the previous year.

The third set of variables included our primary variables of interest: for a given name i, the usage of its first, middle, and last phonemes in names given to babies in the previous year (i.e., F, M, and L in year $t - 1$). In particular, we include lagged terms for both probability of being active ($\beta_{p2} * F_{i,t-1}$, β_{p3} *

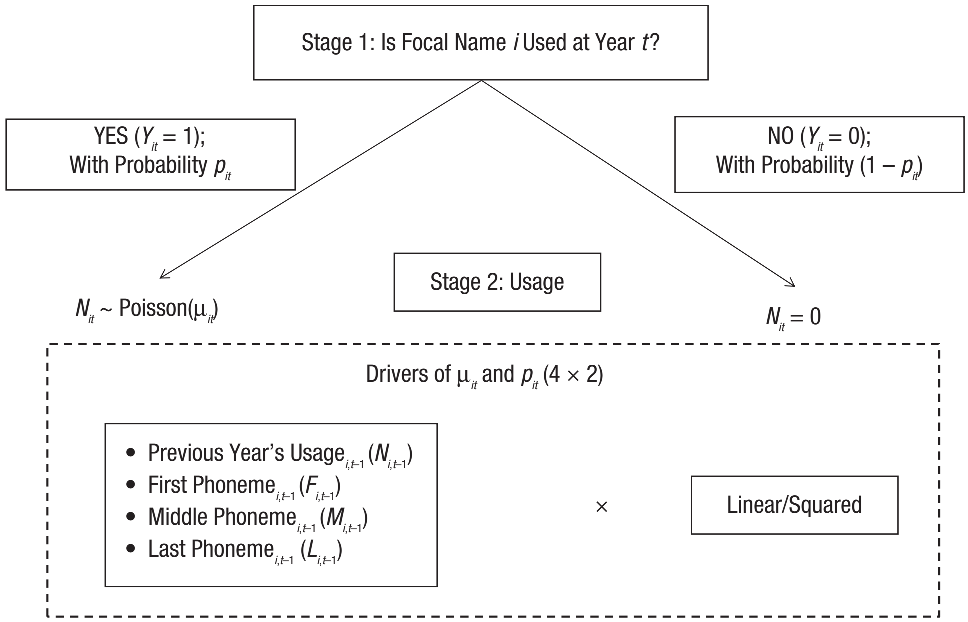

Fig. 2. Two-stage model for name popularity. Stage 1 indicates whether name *i* is "active" in year *t*. If it is active (Y_{it} = 1), Stage 2 indicates the frequency of usage, N_{it}, and its associated predictor variables. See the text for further details.

$M_{i,t-1}$, $\beta_{p4} * L_{i,t-1}$) and usage ($\beta_{U2} * F_{i,t-1}$, $\beta_{U3} * M_{i,t-1}$, $\beta_{U4} * L_{i,t-1}$).[1]

Finally, to test for possible effects of overpopularity, we included both linear and quadratic effects in both the activity and the usage stages. Thus, in addition to the controls for name and time, our explanatory variables formed a model with a 4 (same item; first phoneme, middle phoneme, and last phoneme in the previous year) × 2 (linear, quadratic) design.

Mathematical model and estimation

To account for heterogeneity in effects and small-sample inferences, we utilized a hierarchical Bayesian formulation as follows. For brevity, we describe here only the model for Stage 1 (an identical specification for Stage 2 is provided in the Supplemental Material available online):

Stage 1: potential use (activity) of baby name i at time t, where $Y_{it} = 1$ if name i is active in year t and 0 otherwise

$$Y_{it} \sim \text{Bernoulli}(p_{it}) \quad (1)$$

$$\text{logit}(p_{it}) = \alpha_{pi} + \delta_{pt} + \beta_{p1} * N_{i,t-1} \quad \text{[controls]}$$

$$+ \beta_{p2} * F_{i,t-1} + \beta_{p3} * M_{i,t-1} + \beta_{p4} * L_{i,t-1} \quad \text{[main parameters of interest]}$$

$$+ \beta_{p5} * N^2_{i,t-1} + \beta_{p6} * F^2_{i,t-1} + \beta_{p7} * M^2_{i,t-1} + \beta_{p8} * L^2_{i,t-1} \quad \text{[main parameters of interest]}$$

Inferences from the model were derived by obtaining samples from the posterior distribution of model parameters using Markov chain Monte Carlo sampling.

Results

Figure 3 illustrates the relationship between usage of a name in year t and the popularity of other names that include the phonemes in that name in year $t - 1$. For example, the model predicts the popularity of the name *Karen* in 2000 from the usage in 1999 of names that begin with the /k/ sound, end with the /n/sound, or have /æ/, /r/, or /ə/ internally.

Results showed that even after controlling for their own past popularity, names were more popular in a given year if their component phonemes were more popular in other names the previous year. These cross-item effects were nonlinear, however, and varied with phoneme position (i.e., whether the shared phoneme appears at the beginning or end of the name whose usage was being predicted; see Fig. 4; also see Table S1 in the Supplemental Material). Consider the first phoneme. Figure 4 shows the differential impact of usage of the first, middle, and last phonemes in the prior year, fixing the other variables at their mean observed values (see also Table S1). Increased usage of a name's first phoneme in other names one year had a positive influence on that name's popularity the next year. For example, a shift from a first phoneme being used 100,000 times to its being used 125,000 times in the past year was associated with a 36% increase in name usage. However, the impact eventually waned at around a phoneme usage of 183,000, and then turned negative such that further increases in phoneme usage predicted decreased name usage

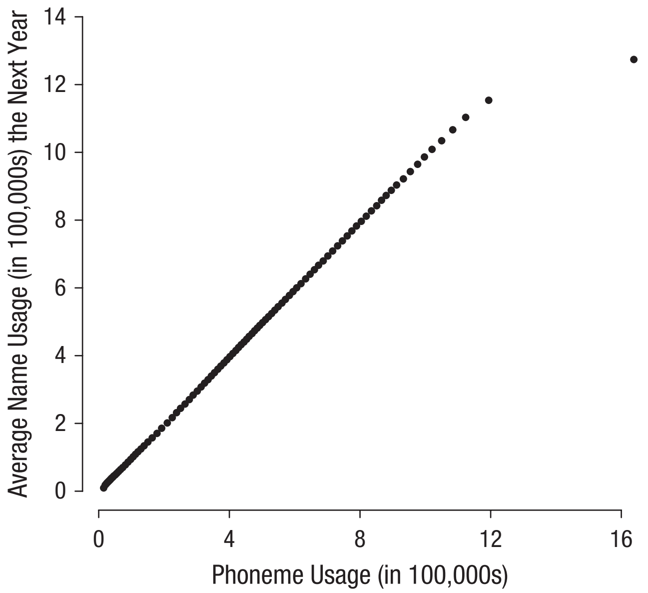

Fig. 3. Average number of babies given a particular name as a function of the number of babies born in the previous year who were given names that include the phonemes in that name. The model from which these predictions are derived included a control for a name's own past popularity. Each consecutive graphed point represents 1 percentile in phoneme usage.

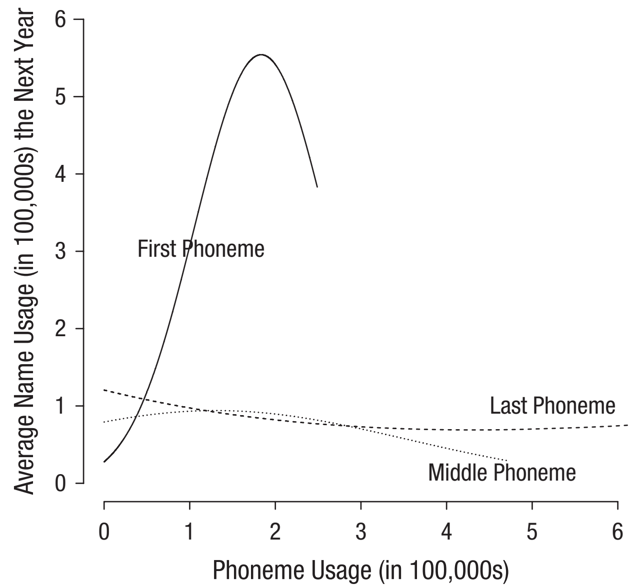

Fig. 4. Impact of phoneme popularity on name usage. The graph shows the predicted average number of babies given a particular name as a function of the frequency with which its first, middle, and last phonemes appeared in other names given to babies the previous year, controlling for the name's past popularity. Predictions are shown for the middle 97.5% of the distribution of the data, leaving off the extremes in each tail.

the following year. This pattern suggests that overpopularity or tedium may kick in after some saturation point (Berger & Le Mens, 2009) and reduce the desirability of particular phonemes.

The effects were considerably smaller for middle and last phonemes ($p < .01$; see Table S1). Thus, although names will be more popular when their last or middle phonemes have been used more in other names the previous year, the usage of a name's first phoneme the previous year has an even greater effect on the name's popularity. This finding is consistent with primacy effects (Perea & Lupker, 2003; Whitney, 2001), whereby earlier things are more salient, receive more attention, and have less lateral interference.[2]

Study 2: Hurricanes As a Natural Experiment

These findings suggest that interitem similarity shapes name popularity over time, but one might wonder whether these relationships are truly causal. To test causality directly, we conducted a natural experiment. We examined how an exogenous increase in the frequency of hearing a phoneme affects the popularity of other names that share that phoneme.

We focused on hurricanes. When hurricanes cause more damage, their names are mentioned more frequently, so their component phonemes are heard more often. Note, however, that hurricanes are automatically assigned names from preexisting lists and are named long before the damages they cause are known. Consequently, a hurricane's occurrence provides an exogenous shock to the frequency with which certain phonemes are heard (there is no effect of prior name or phoneme popularity on hurricane size; see the Supplemental Material). Thus, by examining hurricanes, we were able to investigate the causal impact of a phoneme's frequency on the popularity of names containing that phoneme. We tested, for example, how the incidence of Hurricane Katrina affected the popularity not only of the name *Katrina*, but of all names that begin with a hard *k*, such as *Katie* and *Carl*.

Data

Since 1953, the United States National Hurricane Center has maintained a list of preapproved names for tropical storms and hurricanes. In the Atlantic Ocean, for example, there are six lists of 21 names (each name starts with a different letter from *A* to *W*, not including *Q* and *U*). One list is used every year, and the lists repeat such that each is used every 7th year. Names are assigned to storms in alphabetical order, such that the name of the first hurricane of the season starts with the letter *A*, the next starts with *B*, and so on down the list. When an unusually destructive hurricane occurs, its name is retired and replaced by an alternate name. We collected the names of all hurricanes from 1950 through 2009, as well as data on the amount of damage they caused (adjusted for inflation), from the Weather Underground (2009) Web site.[3]

Hurricane model

We modeled the impact of hurricane damages on the popularity of names that shared phonemes with the hurricane names. The model retained the spike-at-zero structure from Study 1 and added hurricane effects at both stages. In each stage, two parameters were added to capture linear and quadratic effects, respectively. For brevity, we describe only Stage 1 here (the specification of Stage 2 is available in the Supplemental Material):

Stage 1: potential use of baby name i at time t

$$Y_{it} \sim \text{Bernoulli}(p_{it})$$

$$\text{logit}(p_{it}) = [\text{Equation 1 effects}] + \theta_{p2} * HD_{i,t-1} + \theta_{p4} * HD^2_{i,t-1},$$

where $HD_{i,t-1}$ is the sum of the damages caused in the previous year ($t - 1$) by hurricanes whose names shared phonemes with baby name i.

Results

The results provide causal evidence that increased use of a phoneme boosts the success of other names with that phoneme. The more attention a hurricane name received (i.e., the more damage that hurricane caused), the more popular baby names with the same phonemes became (Fig. 5). Following Hurricane Katrina, for example, names that begin with *K* saw an approximately 9% increase in usage. The effect was nonlinear, however, and after a certain point, additional increases in damages no longer increased the popularity of phoneme-sharing names. This suggests a potential trade-off between a positive boost from phonetic familiarity and either overpopularity or the negative connotations associated with an extremely damaging hurricane.

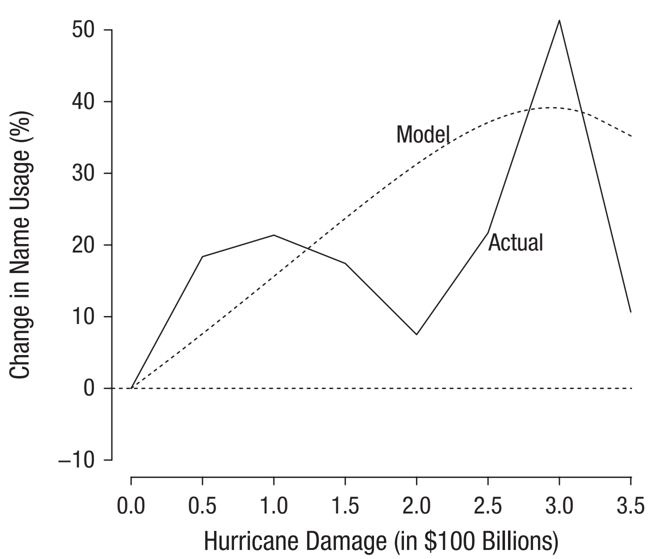

Fig. 5. Average percentage change in the number of babies given a particular name as a function of the damage caused (in $100 billions, in the previous year) by hurricanes whose names included the same phonemes as that baby name. The graph shows both actual change and the model's predictions.

General Discussion

Taken together, these findings suggest some regularity in how culture changes over time. Interitem similarity shapes cultural evolution: Names are more likely to be popular when similar-sounding names have been popular recently. Although we focused on phonetic similarity (i.e., shared phonemes), other types of perceptual and potentially even conceptual similarity may have similar effects. The popularity of the name *Noah*, for example, might drive future popularity of names like *Elijah* and *Isaiah*.

Similar results should also hold in other cultural domains. Songs, technological innovations, and other cultural products may become popular not only on the basis of their own characteristics, or whether they are better or worse than competing items, but also on the basis of whether they sound like, look like, or share common features with other things that have been prevalent recently (Simonton, 1980).

These results underscore the importance of considering the popularity of similar cultural items when predicting diffusion and cultural success. Although prior work has shown that patterns of random copying can predict the aggregate distribution of cultural popularity (Hahn & Bentley, 2003), such models are less useful in predicting the success of individual cultural items. Further, our results (Table S2 in the Supplemental Material) show that including cross-item effects greatly improves model fit and leads to more accurate predictions of name popularity. This indicates that incorporating the popularity of similar items improves predictions of cultural evolution above and beyond modeling the results of random copying, or just considering an item's past popularity by itself.

Variants that are moderately similar to currently popular cultural items may be particularly successful because they provide "optimal" innovation. Repeated exposure to a stimulus increases familiarity and liking of its features, but tedium or satiation eventually kicks in (Berlyne, 1970; Jakobovits, 1966). Further, familiarity boosts preferences more when it is unexpected (Schwarz, 2004). Consequently, moderately discrepant stimuli may have the ideal blend of familiarity and novelty: They are similar enough to evoke the warm glow of familiarity, but different enough to feel fresh and unexpectedly familiar (Flavell, Miller, & Miller, 2001). Names like *Aiden* should be more likely to become popular when names like *Jayden* have been popular recently, and songs that sample or remix other songs may be likely to become hits because they sound familiar yet new. This interpretation also suggests when new cultural items may be created. Names like *Latonya* should be more likely to be created when names like *Tonya* have been popular (Lieberson, 2000). Successful cultural variants often combine similarity on one dimension with differentiation on others.

More generally, this work supports recent theorizing on the psychological foundations of culture (Kashima, 2008; Schaller & Crandall, 2004). When shared across individuals, psychological processes can shape the beliefs, norms, tastes, and institutions that make up culture (Berger & Heath, 2008;

Berger & Milkman, 2012; Heath et al., 2001; Markus & Kitayama, 1991). Along these lines, our investigation shows that preferences for familiarity may underlie the link between interitem similarity and cultural success. Our findings also speak to the reciprocal influence between individual decision making and collective outcomes (Gureckis & Goldstone, 2009). Name popularity influences individual choices, which in turn shape the collective patterns that influence the future choices of other individuals, and therefore cultural evolution.

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Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

Supplemental Material

Additional supporting information may be found at http://pss.sagepub.com/content/by/supplemental-data

Notes

1. In the few cases in which names did not have a middle phoneme, that variable was assigned a value of 0 in the analysis.
2. Results were similar when we measured phoneme popularity over the previous 10 years rather than just the previous 1 year (see Fig. S2 in the Supplemental Material), and when we allowed for cross-position effects.
3. Many hurricanes cause no damage, but in our sample, the mean value of damages from hurricanes that caused damage was $100 million.

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