# Information Resonance

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**Abstract**

People weigh information differently depending on its source. We introduce information resonance—the tendency to use information from sources one identifies with. This affects decisions in finance, education, healthcare, and labor markets. A controlled experiment confirms that resonance extends beyond demographics like gender and ethnicity, influencing decisions based on even minor shared traits. Augmenting a standard information diffusion model, we show that resonance justifies role models, interacts with social networks to reduce expert influence, and when paired with unbiased outcome-based promotion practices, explains homophily in business leadership. Empirical evidence from U.S. labor markets suggests that young workers' occupational choices maybe shaped by socially proximate individuals within their communities. This demonstrates the potential for resonance to have aggregate economic effects.

Individuals and communities with different socioeconomic and demographic backgrounds make systematically different choices across key domains, including education, finance, healthcare, and housing. These differences manifest in major life decisions—whether to attend college, start a family, buy a home, invest in stocks, launch a business, or move to a higher-wage city. Research has consistently shown that individuals are more likely to trust and act upon information when it comes from people they identify with. For instance, Stolper and Walter (2019) found that clients were more likely to follow financial advice from advisors with whom they shared demographic characteristics. Educational choices diverge across communities, house price beliefs have a strong local component, and vaccine uptake depends on social context (Fogli and Guerrieri, 2019; Kindermann et al., 2021; Kuchler et al., 2020b). Numerous examples suggest that information resonates more when conveyed by someone who shares characteristics with the listener. But is that information perceived to be more accurate or relevant? Is this trust or memory? Does resonance operate only along dimensions like geography, ethnicity, and gender, or does it extend to other traits as well? This paper systematically examines the concept of information resonance — how it shapes beliefs, drives actions, and alters outcomes — while probing the boundaries of its influence.

Whether or not people account for information, and how strongly it features in their decisions, depends on the source of the information. This is what we mean by *information resonance*. Some

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information is transmitted, but not internalized. For example, abstractly learned statistics and other information tends to be weighted significantly less than information gathered from personal experiences or the experiences of others whom we care about, identify with or empathize with (cf. Malmendier, 2021a,b; Hertwig et al., 2018; Hertwig and Wulff, 2021). This is not a question of "limited attention" or cognitive limitations, as frequently modeled in economics. Recipients did not "miss" the expert information in question. They might even be able to reproduce and recite it, but it does not resonate with them. They simply do not identify with the person conveying the information. As a result, they put less weight on it in their own decision-making.

This paper takes a multi-pronged approach to studying resonance. First, we use an experiment to isolate resonance and distinguish it from information relevance, memory and trust. The experiment teaches us that many, but not all, personal characteristics can trigger information resonance. Then, we provide a simple framework to better understand the concept of "information resonance" and trace out its logical consequences for behavior. Finally, we present suggestive evidence that resonance matters for aggregate labor market decisions, while highlighting the difficulty of cleanly identifying resonance from non-experimental economic data.

Section 1 presents a lab experiment, which explores what social characteristics trigger resonance. While the existing studies make clear that race and gender matter in decision making, are these the only dimensions along which resonance is strong? One might also wonder whether trust, information relevance or some utility-relevant aspect of personal relationships might explain the results. With these questions in mind, we design an incentivized experiment where subjects need to choose between books they'd like to receive, online courses they'd get access to and even small investments made in one of two funds, based on the advice of a stranger. We provide one piece of evidence about that stranger. The evidence could be their race or ethnicity. But it could also be an array of other characteristics like whether they are a morning or night person, prefer cats or dogs, or even drink Coke or Pepsi. We find that resonance permeates most characteristics and choice contexts. People prefer the option recommended by someone with characteristics similar to them, even when those characteristics have no plausible connection to the choice at hand.

To better understand resonance, we try to push it to its breaking point. How minute and irrelevant can the characteristic be, and still trigger resonance? Where resonance fails is with experiences that are neither chosen nor formative. For example, having broken a bone is not something one chooses, reflects little about the kind of person they are, and is not likely to shape their experiences thereafter. It is an example of an experience that is not deemed to be a characteristic, meaning that it does not trigger resonance.

Section 2 proposes a mathematical representation of resonance that can help trace out its consequences. We model information diffusion, when social proximity determines how much information "resonates," i. e., how much weight individuals put on an action-outcome pair they observe. Using

a standard tools of spatial information diffusion in a Bayesian learning model, social proximity serves as the distance metric and tilts the updating process. We show how role models are powerful because their experiences resonate with many others in their community. The effect is like being a central node in a social network, but without needing any direct social connection between the role model and the observer.

Evidence of the power of role models comes from many domains. In the macro-finance realm, D'Acunto et al. (2021) show that women and Black men update their unemployment and inflation expectations in line with FOMC forecasts when the presence of a woman or Black man on the FOMC is made salient, but White women and Black men *both* respond to the presence of a White woman or a Black man. In the context of education, a plethora of research documents the effects of female and URM (underrepresented minority) "role models" in STEM fields. Having a Black teacher has a positive effect on the educational outcomes of black students (graduation rates and test scores). Furthermore, there are stronger effects of Black male teachers on Black male students and Black female teachers on Black female students (Gershenson et al., 2018), especially in STEM courses (Price, 2010; Carrell et al., 2010). Or, in the context of health decisions, Alsan et al. (2019) found that Black men were more willing to take up preventative care, especially more invasive treatments, after meeting with Black male doctors. Another significant demographic characteristic is political identification, with people feeling close to those with whom they share an ideology. Politically targeted provaccine messaging significantly increased vaccination rates (Larsen et al., 2022).

Next, we use this model to study how this resonance effect interacts with traditional information constraints. Specifically, we explore the effect of social media, which relaxes geographic constraints on information access. Before the advent of social media, someone could only observe their neighbors' experiences. Now, they can connect with anyone. This creates more information for all. However, it is particularly powerful for people in minorities or with extreme social characteristics. Before, they would have found only few geographically close people like them to learn from. They would have been forced to learn from more centrist members of their community, and such learning would have been slow. With the advent of social media, they can weight similar extreme people more, and put correspondingly less weight on the actions of their physical community or on the advice of outside experts.

This insight entails a change in perspective, or relative to prior literature on the effect of social networks. While prior work typically aims to "control for" selection into specific networks, in order to distinguish selection and treatment effects, our model implies that the selection is front and center of their role. People join social networks *because* those spaces are populated by people with a high degree of similarity, whose opinions and experiences they are likely to value. Once social networks are formed, people place higher value on the experiences of those within their

networks. Our theory puts makes selection the key ingredient of interest. It is the characteristics that create the community and drive the exchange of information. We can see the positive effects on members of marginalized minority groups. And we can see the negative effects on fostering extremism, which recent events, such as election fraud myths and vaccine misinformation, have brought to the forefront of public debate. Evidence from Kuchler et al. (2020a) and Bailey et al. (2018) illuminates various ways in which online communities influence beliefs and decisions, e.g., regarding homeownership.[1]

To connect this to measurable economic outcomes, Section 4 uses ACS data (2005–2020) to show that young workers' occupational choices are shaped by same-ethnicity and same-gender elders in their local labor market. If an ethnic group is overrepresented in a given occupation within a Public Use Microdata Area (PUMA), younger members of that group are significantly more likely to enter the same occupation.

To help interpret this result, we further find that the observed effect only holds for same-gender occupational choices; there is no positive influence of opposite-gender over-representation in an occupation. We also show that occupational layoff shocks influence the job choices of the younger generation, only if their ethnicity was overrepresented.

While these findings might suggest that job choices and layoffs among socially close community members resonate more. Despite all the control variables, sample segmenting and differencing, it is difficult to rule out alternative explanations. Correlated occupational choices among same ethnicity-gender-PUMA peers might reflect correlated payoffs. Alternatively, this could be about information access. People learn about the desirability or risk of an occupation from ethic peers and lack access to similar information about other occupations. While we choose specifications to address these concerns, the exercise highlights the need for the experimental evidence to convincingly establish resonance and the domains in which it applies.

Taken together, the paper paints a picture of information resonance - what it looks like formally in a model, what it looks like in aggregate data, and what it looks like in a laboratory setting designed to isolate its effects. Each setting requires a change of focus from information access, to make sense of what is going on. This change in focus, could greatly enhance the effectiveness of a broad array of economic and social policies. The conclusion explains how this simple change of focus could also change the way we think of idea diffusion and the process of economic progress.

**Motivating evidence.** Prior literature documenting that people respond more strongly to others with whom they share demographic similarities comes from several strands of literature on medical, educational, and financial decision-making. In addition to the papers discussed above, several papers in finance point to the role of ethnicity and caste in financing decisions. For example,

[1]Bailey et al. (2018) also noted significant sociodemographic similarities between Facebook friends implying that people select into homophilic social networks.

Hegde and Tumlinson (2014) show that VCs are more likely to invest in startups with coethnic founders, even when these startups are of lower quality. Similarly, Pool et al. (2015) find that mutual fund managers in the same neighborhood hold more similar portfolios, especially if they share the same ethnic background. In India, financial cooperatives are found to maintain caste divisions when forming "joint liability groups," in which members act as guarantors for each other's loans, indicating that people feel more trust and responsibility towards members of their own caste (Stuart, 2007).

Those finding build on a long literature on social learning starting with Bandura (1963). Social learning theories posit that (1) learning occurs when we observe behavior and its consequences (action-payoff pairs in our model), but that (2) it is not pure behavioral imitation (as posited by behaviorism à la Skinner (1938)); rather, the process is affected by the social context (Bandura, 1977). The social context, and how an individual processes the information, depends in turn on characteristics of both the observer and the actor (in the observed behavior or event). In particular, observers are biased towards learning from others they identify with and that are similar to themselves in some way. Similarity has been identified in terms of kinship, familiarity, gender, and language.[2] More broadly, work on how information is transmitted is related to a sociology literature led by Granovetter (1973). A good example of information transmission along ethnic channels arises in a classic case study of Vietnamese nail salons. Workers passed knowledge of how to enter and succeed in this business to others who shared their ethnicity (Federman et al., 2006). Our work proposes a particular modeling structure that provides a lens through which to interpret these studies.

The sociology literature has also anticipated our emphasis on selection effects. Selection effects are important to resonance because they imply that people seek out information from and interactions with those who are similar to them. The sociology literature has dubbed the tendency to connect with and structure social networks around sociodemographic similarities "homophily," which has been incorporated in both theoretical and empirical economic research (McPherson and Smith-Lovin, 1987; McPherson et al., 2001; Kossinets and Watts, 2009; Smith et al., 2014).

In the development sector, literature on information diffusion, particularly "seeding," has shown that community members are more effective than governments in spreading information (Alatas et al., 2016). Not only are they able to spread the information, but they can actually identify which members of their social network will diffuse the information most efficiently (Banerjee et al., 2019). Banerjee et al. (2019) dub these individuals "gossips" and note that while their ability to circulate information is largely due to their diffusion centrality, their position in the network is not at all

[2]For kinship (mother) see Corriveau et al. (2009); for familiarity, or in-group effects, see Learmonth et al. (2005); Corriveau and Harris (2009); Shutts et al. (2009); Buttelmann et al. (2007); Seehagen and Herbert (2012); for gender, see Serbin et al. (2001); Frazier et al. (2012); Shutts et al. (2010); Taylor (2013); for language, see Shutts et al. (2009); Kinzler et al. (2011); Kinzler et al. (2007).

based on leadership status, education, or even their physical location in the village. Moreover, the authors emphasize that diffusion centrality fails to fully explain why gossips are good at spreading information and note that there may be unobserved factors used to identify "gossips," including who is most listened to/trusted.[3]

# 1 Experimental Evidence of Resonance

Previous papers have shown resonance effects arise in specific financial, educational or medical settings, in response to ethnic or gender similarity. But does resonance generalize? Does that type of advice matter? What personal similarities trigger resonance? To explore resonance across a broad range of contexts and exclude other information-quality effects, we turn to a controlled experiment. The results that follow are quite preliminary and subject to change.

In designing our economic experiment, we ensured that several key methodological features were incorporated to enhance the validity and interpretability of our findings. First, subjects made payoff-relevant decisions, ensuring that we are observing economically meaningful choices rather than mere affective expressions of solidarity. Second, we eliminated systematic information in recommendations by fully randomizing the assignment of personal characteristics of recommenders to choices. This was achieved without deception, as all combinations of characteristics and choices occurred naturally in the data. Third, to mitigate demand effects and obscure the purpose of the experiment, subjects reported their own personal characteristics only after making their choices. Fourth, we introduced variation in the choice domains to generalize beyond a single type of decision, incorporating not only charitable giving but also the selection of information sources (books) and consumables (movies and apps), with plans to extend to belief-based bets and investment choices. Fifth, we systematically varied the homophily variables, incorporating both demographic traits deemed highly consequential and more arbitrary personal connections (e.g., preference for cats or dogs). This allows us to disentangle whether observed effects stem from genuine similarity in preferences or from a broader tendency to trust those perceived as similar. Finally, we go beyond simply measuring the rate at which subjects choose the homophilic option by disaggregating these choices based on the specific homophilic trait. This distinction is critical; for instance, if all subjects perceive one political group as a better recommender, and that group is overrepresented in the sample, an apparent homophily effect could emerge spuriously. By incorporating these design features, we ensure that our experiment isolates the mechanism underlying resonance and its influence on decision-making.

[3]Banerjee et al. (2019) find gossips to be incredibly effective at spreading important information. In their trial, villages that used gossip seeding to spread information about vaccinations had 27% higher immunization rates.

## 1.1 Experimental Procedure

The experiment is a 'within-subject' design, i.e. every participant is exposed to every level of the independent variable or to every treatment. In each round, we ask participants to select one of two 'choice variables'. The choice variables pairs consist of the names of different charities, movies, books, and smart-phone apps. We design these choices to be payoff-relevant. That is, we tell participants at the beginning of the survey that we will randomly select 10% of respondents and either donate $10 to one of the charities, or purchase and send them one of their chosen books, apps, or movies selected at random from their choice set.

Below each choice variable pair we display a social characteristic (a 'trivia' or a 'fun fact') of a recommender. We call these pairs of characteristics the 'treatment variables'. They consist of demographic information (i.e. Democrat v. Republican), information about preferences (i.e. prefers working from home or at the office), or information about past experiences (i.e. parents divorced during childhood v. parents did not divorce during childhood). After having recorded the choices of participants, we ask them to also select which treatment variable best describes them for each treatment variables pair.

The key idea is to examine whether stage 2 subjects tend to follow recommendations from stage 1 subjects who share personal characteristics with them. The resonance hypothesis is that subjects will tend to follow the recommendation of the subject with the common characteristic.

**Data, Sample Size, and Implementation** We implement the experiment in two stages. In stage one we ask a sample of participants to choose between choice variables for each choice variables pair and to pick which treatment variable best describes them for each treatment variables pair. The choice variables pairs in stage one are not recommended and do not have data about the recommenders. These choices are also not randomized. We then use the combination of choice variables and treatment variables selections from stage one to display the trivia about the recommenders to stage two participants. Stage one is necessary, because IRB does not allow lying to participants in an experiment.

Stage two, which is the main part of the experiment, consists of a different and larger sample of participants. Participants choose a choice variable for each choice variables pair and then are also asked which treatment variable best describes them for each treatment variables pair. In stage two, as described above, the choices are recommended by a recommender and participants can seek additional information about each choice variable. In addition, the order of the choice variables pairs, the side of the screen of each choice variable within a choice variables pair, the match between each choice variables pair and treatment variables pair, and the match of each choice variable and treatment variable within each choice variables pair and treatment variables pair match are randomized.

Finally, we also allow participants to click on a link that displays more information about each choice variable in a choice variables pair. This additional information consists of a 180 to 200 words long paragraph describing the given charity, movie, book, or smart-phone app. Collecting this information allows us to see whether participants seek more information about the choice variables or they make these payoff-relevant decisions solely based on the information about the recommenders. It also allows us to see whether, conditional on seeking more information, participants want to know more about the choice suggested by the homophilic (recommender has same treatment variable as the participant), the non-homophilic (recommender does not have the same treatment variable as the participant) recommender, or both.

Table A9 lists the full set of personal characteristics we explore, each assigned to one of four categories: preferences, childhood, demographics or personality.

Both stage one and stage two were carried out using Qualtrics software and Prolific participants. Specifically, stage one had a sample size of 100 participants and stage two had a sample size of 250 participants. Participants needed to be American, fluent in English, with a Prolific approval rate (the percentage of a participant's from previous study submissions that are approved by researchers) in the range of 90-100%, and 50% male and 50% female to qualify for either stage one or stage two. In addition, participants who took part in stage one could not participate in stage two. Stage one was carried out on September 16, 2024 and stage two was carried out on September 24, 2024.

### 1.2 Experimental Results

Our findings are consistent with information resonance if participants disproportionately pick a choice variable that is suggested by a recommender whose treatment variable is the same as their own.

Figure 1 illustrates the breadth of personal characteristics that trigger resonance. The dots above 0.5 represent resonance. On average, subjects with these characteristics follow the advice of others who share that characteristic more than others who do not. For example, dog lovers exhibit a higher likelihood of selecting the option recommended by another dog lover than of selecting the cat lover's choice, and vice-versa for those who prefer cats.

The $x$'s above and below the dots are estimates of resonance, estimated separately for each type. In the animal preference example, the average effect is a weighted average of cat-lovers response to the advice of other cat-lovers (lower x) and dog-lovers response to other dog-lovers' advice (higher x). For most characteristics, both types of respondents weight the advice of their own type more heavily. This teaches us that the results do not reflect one type being uniformly regarded are more reliable. One exception is coffee drinkers. Both those who do drink and do not drink coffee are more likely to follow coffee drinkers' advice.

Table 1 shows that resonance effects are statistically significant for each category of personal

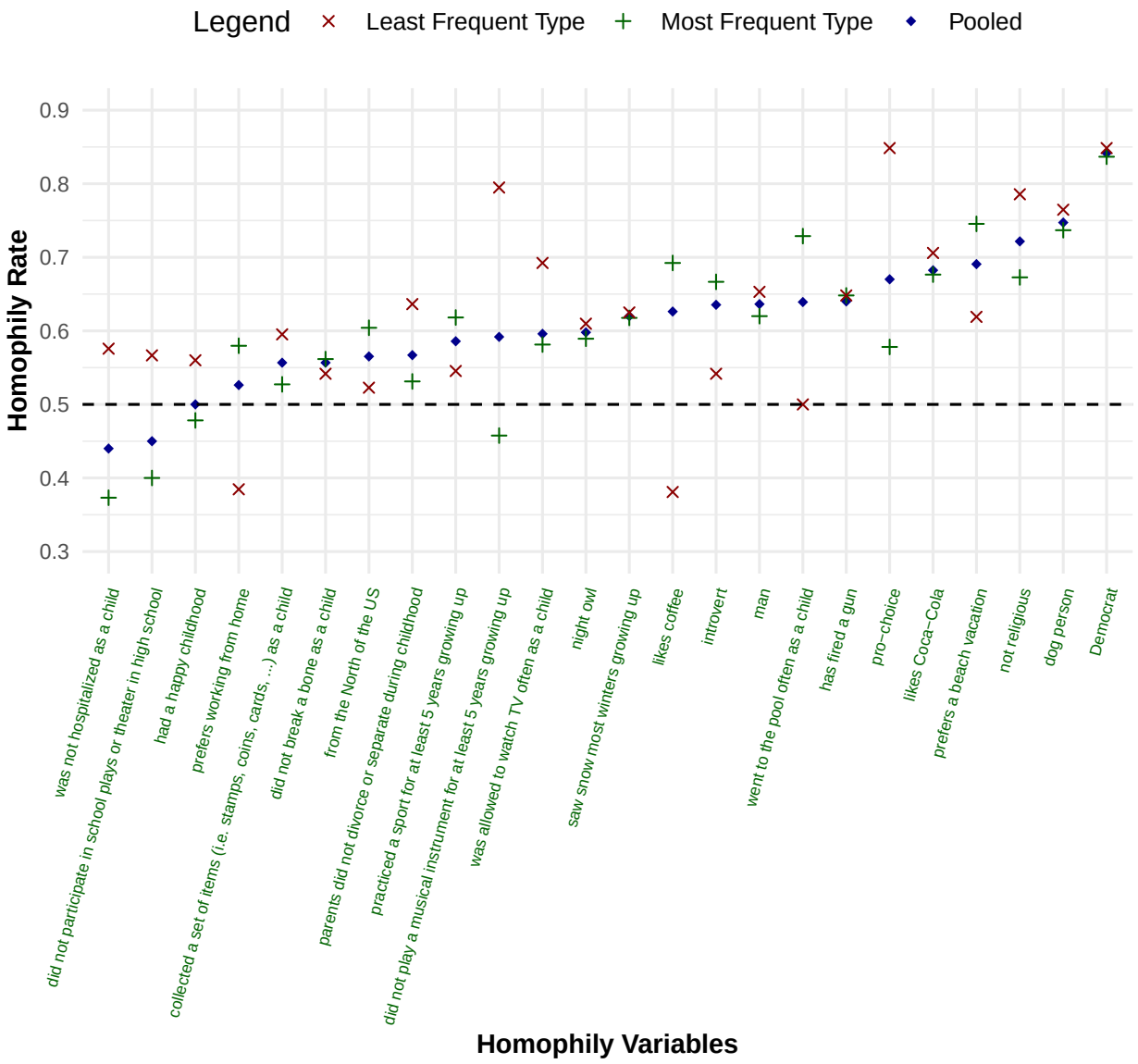



Figure 1: Experimental Resonance: Probability of following advice from others with similar characteristics.

Dots greater than 0.5 represent a greater probability of choosing the item recommended by another subject with similar personal characteristics. $x$'s are the probability of following own-type advice, estimated for each type separately. Personal characteristics listed below each point estimate.

characteristics. (Table A10 in Appendix D reports the full results for every characteristic separately.) However, it also reveals systematic differences in the strength of resonance across different categories of characteristics. The types of demographic characteristics that earlier studies emphasized are indeed the most resonant characteristics. However, preference and personality traits are not far behind, with more than half the strength of demographics. What triggers much less resonance is childhood experiences. People with similar childhood experiences are only slightly more likely to follow the recommendation of others with similar experiences.

Table 1: LPM of Homophily Choice on Homophily Categories.
No intercept, choice Centered at 0.

| | *Dependent variable:* |
|---|---|
| | Homophily Choice |
| Preferences | 0.153*** |
| | (0.027) |
| Childhood | 0.055*** |
| | (0.021) |
| Demographic | 0.183*** |
| | (0.025) |
| Personality | 0.125*** |
| | (0.030) |
| Observations | 2,305 |
| $R^2$ | 0.060 |
| Adjusted $R^2$ | 0.058 |
| Residual Std. Error | 0.485 (df = 2301) |
| F Statistic | 36.494*** (df = 4; 2301) |

*Note*: *p<0.1; **p<0.05; ***p<0.01; Individual-level clustered standard errors (HC1) in parentheses.

These results paint a nuanced picture of what the resonance weights $\omega_{ij}$ look like. We learn that weights on others' information is high when agents $i$ and $j$ share demographic characteristics. That weight is moderate when others share preference or personality characterisitics. The resonance weight is low when there are no similarities or the only similarity is a childhood experience. But overall, they strongly support the hypothesis that resonance exists and affects decisions. The set of factors that trigger resonance is larger than previous studies taught us. Resonance extends far beyond gender and race. Human beings find connections in all sorts of similarities. These connections shape the way we make decisions.

### 1.3 Interpreting the Experimental Results

The findings of this experiment suggest that the observed behavior cannot be attributed to conventional explanations such as information frictions, memory limitations, or trust-based considerations. While one could argue that any single pair of shared traits between individuals might be relevant to the decision at hand, it is highly implausible that the same rationale would apply consistently across all observed pairings. This suggests that the mechanism driving these results is not an issue of incomplete or asymmetric information. Furthermore, memory constraints do not play a role, as the relevant information is immediately accessible to participants, eliminating the need for retention or recall.

Likewise, the results do not appear to stem from trust. The recommendations were provided anonymously, with neither the recommender nor the recipient knowing one another. Since there was no potential for a conflict of interest, participants had no rational reason to distrust or devalue the advice based on concerns about the advisor's motivations. In the absence of these conventional explanations, the most plausible interpretations of the observed behavior center on preference or habit.

One possibility is that individuals exhibit an intrinsic preference for acting on information provided by those who share their characteristics. Alternatively, the behavior may reflect a heuristic—a rule of thumb developed from other contexts where information from similar individuals is indeed more relevant. In many real-world settings, shared characteristics can serve as useful signals for preference alignment, such as in product recommendations or lifestyle choices. However, in this experimental setting, those characteristics do not enhance the relevance of the information, yet they still influence decision-making. This suggests a systematic cognitive bias—one that, while often adaptive, can be misapplied in contexts where similarity does not equate to better information. Such a bias could have significant implications at the aggregate level, shaping societal decision-making processes in ways that are not necessarily optimal.

## 2 Model

The model is simple. It makes one small change to a standard model of Bayesian updating with information diffusion. This simplicity allows our mechanism to be easily incorporated into other settings. The goal is not to innovate technically, but rather to show how existing tools can be adapted to capture resonance. The subsequent section shows how resonant learning can differ from a more standard information access, geographic diffusion model, by exploring the power of role models. Next, it combines information frictions and resonant learning to show how the rise of social networks can undermine the influence of experts. Finally, we extend the model to show how it can be a foundation for labor market discrimination.

In order to make these arguments, our model needs to have the following ingredients:

1. Agents are uncertain about the distribution of a stochastic payoff.
2. Agents learn from observing experiences (action-payoff pairs) of other agents in the economy, including their own.
3. Agents with heterogeneous characteristics $\theta$ weight the information that comes from others with nearby characteristics more heavily.

Further, in order to compare our mechanism with a traditional information friction, we add variation in the access to information, as a feature that we can turn on or off.

**Payoffs.** Agents make decisions between two possible actions: a known baseline action (e.g., maintaining the status quo) and a new action (e.g., adopting a new technology, changing occupations, or receiving a vaccine). The expected payoff from the new action is uncertain, with a persistent component (individual-specific) and a random transitory component.

Each agent $i \in \{1, \ldots, N\}$ chooses one of two actions $a \in \{0, 1\}$. The payoff to action $a = 0$ is known, and we normalize its payoff to be 0. In other words, the payoff to action 1 can be interpreted as its excess payoff over the payoff to action 0. The payoff to action 1 has two components, both of which are unknown to agents: There is a permanent component $z_i$ that agents can learn about and a transitory component $\epsilon_{it}$ is that is i.i.d. over time and thus unlearnable.

Let $z$ be the vector of all agents' payoffs, and $z_i$ its $i$th entry. Agents have priors $z \sim N(\mu_z, \Sigma_z)$, where $\Sigma_z$ is a variance-covariance matrix. If all agents have the same persistent payoff from an action, then $\Sigma_z$ should have every entry with an identical value. If agents have payoffs from action 1 that are entirely independent, and they cannot learn anything from others' experiences, this would be a diagonal $\Sigma_z$ matrix. Agents choose action $a_{it}$ to maximize their expected payoff:

$$U(a_{it}) = a_{it} E[z_a + \epsilon_{it} | \mathcal{I}_{it}]. \tag{1}$$

where $\epsilon_{it} \overset{iid}{\sim} N(0, \sigma_\epsilon^2)$ is the unlearnable random part of payoff, which is time- and individual-specific. Without the unlearnable payoff shock, one observation of an action-payoff pair would reveal exactly what the payoff $z_a$ is for a chosen action. The random payoff $\epsilon_{it}$ is what makes learning a gradual process.

**Information sets.** If agent $i$ takes the action $a_{it} = 1$ at time $t$, then each agent $j$ potentially sees their action and payoff outcome. Define an observation matrix $\Psi_t$, where the $(i, j)$th entry of $\Psi_t$ is 1 if $i$ observes $j$ and $j$ takes action $a_{jt} = 1$.

$\Psi_t$ might have a component that is not time-varying. For example, if $i$ sees only people in her neighborhood or only facebook friends, then $\Psi_t$ is the element-by-element product (a Hadamard

product) of the social network matrix – a stable matrix of zero's and ones that indicates social connections – and the matrix $\mathbf{a}_t\mathbf{1}_n'$, where $\mathbf{a}_t$ is a $n \times 1$ vector of every agent's time $t$ action and $\mathbf{1}_n'$ is a $1 \times nh$ vector of 1's. Alternatively, we can consider people who are randomly visible. Or celebrities who are visible with a higher probability than others. This would be captured by a $\Psi_t$ matrix with a random component.

To express our solution, we need a bit of additional notation. Let $K_{it}$ be the number of $a = 1$ actions agent $i$ observes at time $t$. Then, $K_{it}$ is the sum of the entries in the $i$th row of $\Psi_t$. Then define $\psi_{it}$ to be a $K_{it} \times N$ matrix. Each row is a $N$-dimensional vector of zeroes, except for a one in $j$-th column, if $j$ takes action $a = 1$ and $i$ observes $j$'s payoff. This is a re-shaping of the $i$th row of the $\Psi_t$ matrix. This related matrix will be useful to express the model solution. We can express the set of signals that agent $i$ sees about the payoffs to action 1 as $\psi_{it}(z + \epsilon_t)$. This product is the $K_{it} \times 1$ vector containing a subset of the entries of the $N \times 1$ vector of all payoffs that agent $i$ gets to see.

The economic content of these assumptions is simply that everyone who observes agent $j$ take action $a_{jt} = 1$ observes an informative signal about $z_j$, which they can use to infer their own payoff component $z_i$.

**Belief updating** In this framework, $\omega_{ij}$ captures the extent to which agent $j$'s information resonates with agent $i$. A higher $\omega_{ij}$ means that $i$ assigns more weight to $j$'s experience when updating their beliefs, due to stronger perceived social proximity. For agent $i$ taking action $a = 1$, belief updating takes the form:

$$E[z_i|\mathcal{I}_{it}] = \alpha_{iz}\mu_z + \overline{\omega}_{iz}\sum_{j=1}^{N}\sum_{t'=1}^{t}\omega_{ij}\beta_{izj}(z_j + \epsilon_{jt'}), \tag{2}$$

where $\alpha_{iz}$ and $\beta_{izj}$ are the Bayesian weights on priors and signals:

$$\beta_{iz} = (\mathcal{Z}_{it}\Sigma_z\mathcal{Z}_{it}' + \sigma_\epsilon^2 I)^{-1}\mathcal{Z}_{it}\Sigma_z\mathbf{1}_i \;\; = \;\; \frac{Cov(z_i, z + \epsilon)}{Var(z + \epsilon)} \tag{3}$$

$$\alpha_{iz} = 1 - \sum_{j=1}^{N}\beta_{izj}. \tag{4}$$

The indicator variable $\mathbf{1}_i$ is a $N \times 1$ vector of zeros with 1 in row $i$, and $I$ is an identity matrix with size $K_{iz}$. The second equality in (3) shows that the Bayesian weight on signals is simply the standard OLS estimator derived from linear models.

$\overline{\omega}_{iz}$ is a normalization factor such that:

$$\overline{\omega}_{iz} \sum_{j=1}^{N} \sum_{t'=1}^{t} \omega_{ij} \beta_{izj} = \sum_{j=1}^{N} \sum_{t'=1}^{t} \beta_{izj}. \tag{5}$$

This normalization makes sure that prior belief gets the same weight with or without resonance, and it also allows $\omega$ to be scale-neutral.

The $\omega$ term is the piece that is new to our theory. It is the weight someone puts on the observed experience of another person. In standard Bayesian learning models, the prior and each signal are typically weighted by their precision, the inverse of their variance, and divided by the sum of precisions, to get a weighted average. In our "neurologically realistic" Bayesian model, the conditional expectation is still a weighted average, but the agent adjusts the Bayesian weight for each signal by $\omega$. As we will specify below, this term allows us to account for agents giving less weight to information that comes from sources who are dissimilar. The fourth and final term in the expectation is the signal $z_a + \epsilon_{ajt'}$, the noisy information transmitted about the payoff to action $a$.

**Belief weights and characteristics.** For an observer $i$, different observations have different relevance. When $i$ observes $j$, the weight $i$ places on that observation, $\omega_{ij}$, depends on the distance between the characteristics $\theta_i$ of the observer and the characteristics $\theta_j$ of the person who took the action.[4] Then, if $i$ observes $j$'s actions,

$$\omega_{ij} = \underbrace{(2 - 2\Phi(\chi||\theta_i, \theta_j||))}_{\rho_{ij}} \cdot \sigma_\epsilon^{-2} \tag{6}$$

$$= \qquad \rho_{ij} \qquad \cdot \sigma_\epsilon^{-2}, \tag{7}$$

where $||\theta_i, \theta_j||$ is the Euclidean distance between agents' characteristics $\theta_i$ and $\theta_j$.[5] The multiplicative term $\chi$ allows us to consider different scenarios of agents weighting own versus other experiences more or less, as we discuss in more detail below. The Normal cumulative distribution function $\Phi$ equals 1/2 at 0, and hence the expression $2 - 2\Phi(\cdot)$ takes on a value of 1 at zero and then declines quickly towards zero. These terms define the resonance, or relevance, $\rho_{ij}$ that a signal coming from $j$ has for observer $i$.

We scale the resonance weight $\rho$ with the (true) accuracy of the signal, $\sigma_\epsilon^{-2}$, to reflect the idea

[4] What $w$ and $\theta$ should not capture is access to information. Some characteristics might, however, also determine access. For example, language, geographic location, and socio-economic status can determine the set of people they can observe. If this is the case, we would capture the informational friction via the information access matrix $\mathcal{Z}_{it}$, which would be related to the entries of $\theta_j$.

[5] One might think that agents should also learn from each others' choices, not just the outcomes. For example, if $i$ sees that $j$ did not choose action 1, $i$ might infer that $j$ has negative information about action 1. That sort of inference does not happen with pure resonance because resonance is not about asymmetric information. Everyone sees the same outcomes. They simply put different weights on them. When we also introduce information asymmetry, this becomes an issue, unless we define communities where if $i$ sees $j$, then $i$ also sees the same community outcomes that $j$ sees. Then, within observation groups, there is not information asymmetry and nothing to be inferred from choices.

that agents will not weight signals that have no information content at all. Thus, the overall weight $\omega_{ij}$ is the product of the resonance weight $\rho_{ij}$ and the precision weight $\sigma_{\epsilon}^{-2}$.

**Equilibrium** Everyone acts simultaneously in every period, knowing the outcomes of the previous periods. Agents maximize expected utility as specified in (1). They update their prior of the unknown payoffs $z_a$ for each action $a$ using Bayes' rule as spelled out in equations (2), with weights $\omega_{ij}$ as defined in (6)-(7).

Note that our agents are myopic. When they choose an action, they are not considering how much information that action will generate to enable better decision making for themselves or for others in the next period. The sort of active experimentation that we rule out here would greatly complicate the analysis, would obscure the main mechanism and would likely have minimal effect on results because of a free rider problem: When everyone can see actions of many others, the incentive is to let others incur the cost of experimentation and learn from their results.

**Comparing related learning mechanisms.** Our model of resonant information can nest other popular versions of information diffusion. At one end of the spectrum, our model allows for people place zero weight on anyone's experience other than their own, namely, when $\chi$ becomes very large. Only personal experiences in the sense of the payoff realizations resulting from own action choices affect beliefs (as in Malmendier and Nagel (2011, 2016)). At the other end of the spectrum, $\chi = 0$ represents the scenario where people learn from everyone's experience collectively, without discounting anyone's information. Theories of belief scarring show that when we learn from our collective experiences, transitory but extreme outcomes can have long-lived effects on aggregate outcomes (Kozlowski et al., 2020).

In between these polar cases, cities or metropolitan areas have beliefs that evolve differently because of their different experiences (Chodorow-Reich et al., 2021). If we think of the characteristic vector $0 < \chi < 1$ including one's location or metro area, the model becomes one of local learning from neighbors, as in (Fogli and Veldkamp, 2010; Burnside et al., 2016).[6]

Dynastic learning (Boerma and Karabarbounis, 2017) is also encapsulated by this framework. The characteristic space would include only whether one is a member of the same family, or not. If $\theta = 1$ for family members and $\theta = 0$ for all non-family members, then for $\chi$ very large, learning is dynastic.

Information resonance also helps to remedy a perpetual problem with Bayesian updating. In a standard Bayesian updating problem, a small amount of information will correct beliefs very

[6]While the neighborhood-based cost functions of Hebert and Woodford (2020) sound similar, their focus is on how difficult it is to tell apart two states of the same world, that might lie in the same neighborhood, in event space. In contrast, we have a standard treatment of states of the world and focus instead on the characteristics of one's information sources.

quickly. Since all agents give full weight to all observations, a few realizations can induce quick convergence in posteriors. This is problematic because real people do not learn this efficiently. One advantage of weighting information by its resonance is to make information effectively scarce. People see lots of outcomes; but much of what they see does not resonate, and is therefore largely ignored. That slows changes in community behavior in a realistic way.

*A rational interpretation.* Our representation nests a rational one, where resonant information is simply more statistically relevant information. Characteristics could be loadings on payoff factors such that the distance metric $\omega_{ij}$ reflects the extent to which $i$'s outcomes covary with $j$'s. In that case, our model would capture rational econometric learning, with a known covariance structure of outcomes across the population. The weight on a piece of information about another agent's experience would then be covariance, divided by variance, which is a standard ordinary least squares regression coefficient. The belief formation rule (2) would become an ordinary least squares forecast, given all observed information. The variable $\theta_j$ can be a vector that includes any or all of these characteristics. However, our experiment highlighted settings where characteristics do not affect statistical relevance.

# 3 Properties of Resonant Learning

This section explores numerical examples of the dynamic learning model. The goal is not to quantify, measure or prove that any particular dynamic arises, but rather to illustrate some interesting consequences of resonance that resemble real-world phenomena.

We start by contrasting the essential difference between "information resonance" and the traditional emphasis on "information frictions," and then explore how the two forces interact. Information frictions prevent people from obtaining, or observing, information. Information resonance captures how people weight the information they see. When information access changes, people can access more resonant information. This causes them to downweight less resonant, but more reliable expert opinions.

## 3.1 Parameter Choices and Procedure

We choose parameters, without any attempt to match realistic values. These are numerical examples designed not to measure any effect, but simply to illustrate the qualitative mechanics of this mechanism.

The parameters we use are as follows: Action payoffs are 0 for action $a = 0$ and $z_i = 4\ \forall i$, meaning that all agents have the same persistent component of payoffs to action $a = 1$. The individual transitory shocks to payoffs are very noisy, with $\epsilon_{ait} \sim N(0, 100)$ for both actions $a$, independently drawn for actions, agents, and time. Thus, in the absence of taxes or subsidies the

total payoff to actions, net of action costs are: Action 0 has payoff $\sim N(0, 100)$. Action 1 has payoff $z_1 + \epsilon_{it} \sim N(4, 100)$. That is, action 1 is the better (higher expected payoff) action. If agents knew the true value of $z_1$, they would maximize their utility, as specified in (1), by choosing action 1. Prior beliefs for action 1 are $z_1 \sim N(-3, 10)$. So agents believe that action 0 is superior, when in truth, it is not. The action costs and subsidies are known to all agents. Agents update their beliefs according to (2).

The probability of agent $j$ observing agent $i$ at time $t$, $\Pr[\psi_{jit} = 1]$ is initially set to 0.2. In other words, all action-outcome pairs have a 20% chance of being observed by any given other agent. Finally, the distance between any two vectors $\theta_i$ and $\theta_j$ is transformed by parameter $\chi = 0.2$.

The simulations below differ only in their initial conditions, including the distribution of characteristics (uniform or normal), the presence of taxes (or subsidies). What they all share in common is the following procedure:

1. For 400 agents, assign each node a geographic location $(x, y)$ on a 20 x 20 grid. Create a matrix where each node has a row and column that represent its physical location on a two-dimensional plane. This implies that the geographic distribution is uniform.

2. Draw social coordinates $(v, w)$ for each of these nodes. To achieve an even distribution of characteristics, Figures 1 and 2 draw $(v, w)$ from the two-dimensional integers $[0, 0]$, $[20, 20]$, without replacement.

3. Given these initial conditions, each agent chooses the action with higher expected payoff.

4. Draw random payoff shocks $(\epsilon_{it})$ for each chosen action.

5. Allow agents to observe the total payoff $z_j + \epsilon_{jt}$ for each $j \epsilon \tilde{\mathcal{Z}}_{it}$. Add this new data to each agent $i$'s information set and update each agent's beliefs, according to (2).

We repeat this procedure for 20 periods, and repeat the entire simulation, starting from the date-0 initial conditions, ten times. For each node at each date, we report (and illustrate graphically) the fraction of simulations in which that node chose action 1. This averaging of results allows to smooth out some of the randomness of a particular simulation.

More details on the simulation procedure for each set of results are in Appendix B.

### 3.2 Experts vs. Role Models

We now illustrate the basic insight emerging from our learning mechanism: the differing influences of "access to information," which is at the core of many traditional learning models, versus "social proximity" (information resonance) to the underlying realizations. We start by describing the model's characteristic space topology.The technical insight is that after re-casting the outcomes in this new topological space, resonance functions just like an information diffusion friction.

We denote someone whom many people feel socially close to a 'role model.' Their actions and experiences resonate with many people. That is, others put significant weight on and thus learn from the information provided by role models. We contrast the role model with a person about whose action and experiences many people are informed about, which we dub a 'celebrity.' The contrast between the influence of role models versus celebrities mirrors the difference between the effect of "social proximity" (information resonance) versus "access to information" that we would like to illustrate. Examples of such local influence on public health abound in the popular press, from the role of rabbis among ultra-orthodox Jews in Israel, Aboriginal health organizations in Australia, to local leaders in the rural areas in the U.S., Union leaders in Harlem, and descendants of participants in the Tuskegee study in Alabama. More evidence of the power of role models is reported in Appendix E.

Because the leader's characteristic similarity leads others to put more weight on their experience, getting the one local leader to switch actions brings about faster learning and a faster change in actions from the community. This illustrates the power of resonant information and contrasts it with access to abundant information that does not resonate with a given community.

*How many distant examples are equivalent to the example of one local leader?* Turning from the specific numerical example in our simulation to the more general point about the power of local leaders, we consider a theoretical exercise with general parameters. Consider a community where members' characteristics are evenly spaced on an $n \times n$ grid. Suppose all actions are fully visible ($\Psi = 1$). Initially, at time $t = 0$, every agent in the community chooses action 0. Since action 0 has been chosen many times in the past, beliefs about action 0 are precise ($V[z_0|\mathcal{I}_0]$ small). Now consider two alternative scenarios:

At date $t = 1$, either

1. A local leader, located in characteristic space at $(\lfloor n/2 \rceil, \lfloor n/2 \rceil)$ takes action 1, where $\lfloor \cdot \rceil$ represents rounding to the nearest integer; or

2. $\tilde{J}$ adjacent neighbors, each $\gamma > 1$ spaces away from the nearest community member, in characteristic space, all take action 1.

Define the weight that the community members closest to the local leader put on the local leader's experience as $\omega_{ll}$. Similarly, denote the weight that the community members closest to the neighboring community members put on the experience of such neighbor as $\omega_n$.

**Proposition 1.** *In order to have an equal probability of getting the nearest community member to switch to choosing $a = 1$ at date $t = 2$, as one local leader in scenario 1, it requires $\tilde{J}$ neighbors in scenario 2, where $\tilde{J}$ solves*

$$Q_1 \tilde{J} + Q_2 \tilde{J}^{1/2} + Q_3 = 0,$$

*with* $Q_1 = \omega_n(E[z_0|\mathcal{I}_0] - z_1)$, $Q_3 = \sigma_1^{-2}(E[z_0|\mathcal{I}_0] - \mu_1)$, *and* $Q_2 = (\omega_n/\omega_{ll})Q_3 - Q_1$.

This result teaches us that there are two effects to consider when comparing a single local leader to many distant experts. The first effect is that the local leader resonates more. The resonance of the neighboring nodes can be seen in the $Q_1$ term, where the difference between beliefs about the benefits of action 0 and the average realization of payoff to action 1, $E[z_0|\mathcal{I}_0] - z_1$, is weighted by the information weight of the neighbor. The $\tilde{J}$ signals from the more distant agents each convey, on average, that the payoff to action 1 is higher, by the amount $(z_1 - E[z_0|\mathcal{I}_0])$, weighted with $\omega_n$. The higher resonance of the local leader shows up as a lower value of $\omega_n/\omega_{ll}$.

If the relative weights were the only effect at work, the result would be that $\tilde{J} = \omega_{ll}/\omega_n > 1$. In other words, if a local leader resonated twice as much, then there would need to be twice as many neighboring examples to achieve an equivalent degree of persuasion.

The second effect, and the reason the answer is not that simple, is that having multiple observations from highly visible (albeit socially distant) information providers achieves something like a central limit theorem effect. Each observation of a person's experience has individual-specific noise, with variance $\sigma_\epsilon^2$. The noise of the sum of $\tilde{J}$ neighbor's experiences has standard deviation $\tilde{J}^{1/2}\sigma_\epsilon$. In our adapted information weighting scheme, this shows up as $\tilde{J}^{1/2}(\omega_n/\omega_{ll})$. Thus, the solution incorporates both effects.

Both the theoretical result and the numerical example convey the power that local leaders, with characteristics that are similar to their communities, have to inspire a change of behavior in their communities. But they also show that access to information has a distinct advantage: With more sources of information, an observer can average out most of the individual-specific noise.

### 3.3 Resonance with Information Frictions: Social Networks and the Decline of Expertise

In our last theoretical exploration, we examine the interaction between information access and information resonance. Online social networks have affected a radical change in information access in the last two decades. The model clarifies how these online social network platforms interact with resonance.

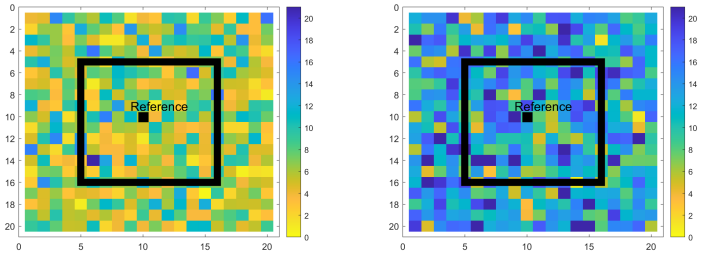
Prior to the digital era, access to information was constrained by geography. It was hard to learn news about the community you grew up in once you moved away. For people not part of the local majority group, it was difficult to find resonant information. In the social network era, people can form communities without geographic constraints. At the same time, the influence of experts declined. Resonance offers an explanation for this decline.

To capture the changing relevance of geography and the endogenous selection into networks in our model, we modify the information access matrix $\mathcal{Z}$. If agents $i$ and $j$ are close enough to each other in location to communicate, we set $\mathcal{Z}_{ij} = 1$ (full visibility). Otherwise, $\mathcal{Z}_{ij} = 0$.

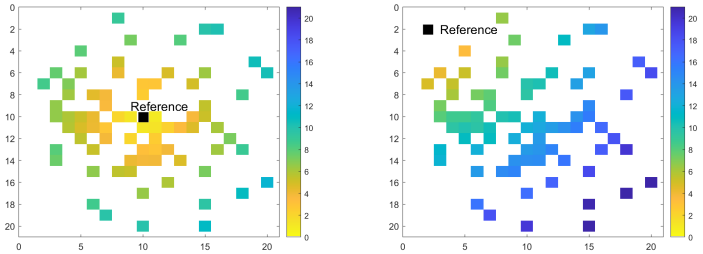
*Simulation details.* The agents are distributed uniformly in geographic space, with one person assigned to each node in a grid. However, while characteristics were assigned uniformly in the pervious simulations, they are now normally distributed. The reason for this change is that we want to illustrate the differential impact of social networks on members of the majority community and those in the minority ("in the tails"), such as ethnic or racial minorities or political extremists. Specifically, we draw two characteristics $v$ and $w$ from the distribution $N(10, 5)$. When we plot agents in characteristics space rather than geographic space, we assign each agent to the node with the closest integer value. For example, if an agent draws $(v, w) = (2.7, 9.1)$, they are assigned to the $(3, 10)$ on the characteristic grid. In many cases, multiple agents are assigned to the same box. The number of agents assigned to a box is not visible on the plot, but it is systematically higher at the center of the grid since many agents draw characteristics closer to the mean. Around the edges of plots in characteristic space, instead, there will be many white (empty) boxes indicating cases where no agent drew characteristics in this space.

An centrist agent (left) and one with extreme characteristics (right) plotted

(a) in geographic space:




(b) in characteristic space, with geographic information constraints:




(c) in characteristic space, with no information constraint:

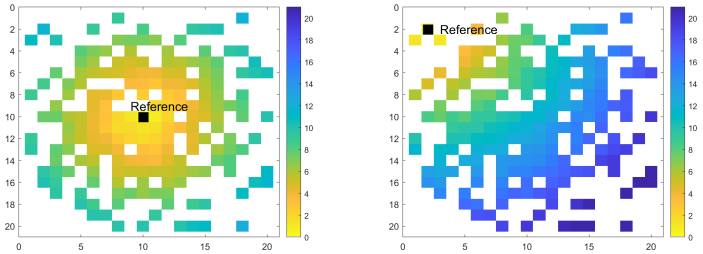



Figure 2: Social proximity in geographic and social space. Extreme agents get far more information flow when geographic constraint is relaxed. Social proximity to a reference person is represented in warmer colors (yellow tones); social distance in cooler colors (blue tones). The black frame in Panel (a) represents the geographic restriction (with $\Psi = 1$ inside the frame, and $\Psi = 0$ outside the frame) prior to social networks. The middle plots in Panel (b) include only geographically nearby agents (those inside the black frame in Panel (a), i. e., with $\Psi = 1$), plotted in characteristics space. The bottom two plots in Panel (c) include both geographically nearby and distant agents.

Figure 2 illustrates the differential effect of social networks on members of the majority and the minority groups. In Panel (a) (top row), we plot community members according to their physical (geographic) location. One agent lives at each node. Differently from prior figures, we use colors to illustrate social proximity relative to a reference person, shown as a black dot at the center of the grid. (Note that the inital location geographic has no particular significance. We are just examining the 20-by-20 neighborhood around a given agent's location.) Warmer (yellow) tones indicate social proximity, and cooler (blue) tones indicate social distance, and each agent is given

a color, according to their social proximity to the reference point. The variegated color pattern on the geographic topology represents the fact that social type and geographic location are not correlated in this example.

The difference between the left and right panels is that the reference agent in the left panel is central not just geographically, but also socially. This person has a low social distance to many other nodes, represented by the high frequency of warmer colors on the top left. The person on the right, instead, has more extreme, or minority characteristics. Because characteristics are normally distributed, the density of other agents in the nearby social space is lower. Extremists see fewer people like them. Most of their geographic neighbors have a high social distance, represented by the cooler colors on the right.

Focusing at first on the agents inside the black frame ("pre-Facebook"), we re-plot all such agents in their respective colors in characteristics space in Panel (b) of Figure 2. These panels show the social proximity of observable community members, i. e., those inside the black frame, both in color and spatially. They are then weighted according to how resonant their information is. The empty (white) boxes are characteristics pairs not represented by any agent to whom the reference person is connected. Note that, in the left graph of Panel (b), the reference person remains centrally located also in characteristics space. This reflects that we picked a socially central person, akin to the local leader in Section 3.2 before. In the right graph, instead, the reference person moves to the upper left corner in characteristics space. This reflects that we picked a socially more isolated, or outlier set of characteristics. Here the reference person has extreme characteristics and is thus located at the fringe of the social space.

Next, consider the effect of widened communities, due to social networks. In Panel (c), we allow the reference node to connect to all agents from Panel (a), whether inside our outside the black frame. The change can be interpreted as representing the ability of social media to connect across large geographic distances. Correspondingly, the bottom two panels show the social location of all nodes from Panel (a), just in different locations, representing their social distance from the reference node. Note that some locations on this plot have multiple nodes, representing multiple agents in that characteristic space location. Other nodes remain white since no agent has the corresponding characteristics. Naturally, we now see fewer white boxes. Relaxing the geographic constraint on information access allows a denser set of agents to be observed. This relaxation of the geographic constraint is meant to represent the way in which social media allows for communication and community formation, without regard to geographic location.

**Social Networks and Social Outliers** The stronger reaction of outlier (minority) communities to changes in information access is a key prediction that distinguishes our mechanism from information frictions. While relaxing geographic constraints gives all agents access to more information, the effect is much stronger for social outliers. These are agents who have scarce access to trusted

information sources, when their community is geographically restricted.

**Proposition 2.** *Expert actions have more influence on others' beliefs when agents are geography-constrained ($\partial E[z_a|\mathcal{I}]/\partial a_{celeb}$ larger).*

The proof is in Appendix A. The idea is that geographic constraints limit agents' data points. With fewer relevant data points, each one gets more weight.

Figure 2 illustrates the logic of this result. This scarce resonant information is the large number of white boxes and few warm-colored boxes around the reference agent in the center-right pane of Figure 2. Giving extremist agents like the reference agent on the right access to information from geographically distant but socially proximate agents greatly increases their resonant-information set (bottom-right panel). For the same reason, it also greatly decreases the weight they place on information from authorities.

The difference between the left and right columns of panels in Figure 2 is that the left column agent is socially central. This is someone in the majority. Since social characteristics are normally distributed, someone near the average has a high density of socially proximate neighbors. In contrast, on the right of Figure 2, the reference agent has outlier social characteristics. Because they are located in the tail of the normal distribution, this agent has fewer socially proximate neighbors to identify with and learn from. When social media relaxes the geographic constraint on information access and allows this agent to observe all nodes, some resonant information sources (yellow boxes) appear. This person with extreme characteristics will now place more weight on those resonant sources of information and less weight on all other information, including reliable and informed authorities.

### 3.4 Resonance as a Foundation for Labor Market Discrimination

Finally, we study how resonance could explain discriminatory outcomes. If someone in power responds more to the recommendations of others that share their traits, that bestows the power of influence with these same-trait employees. If all employees' recommendations are are equally good, same-trait employees will create more value by triggering more positive change. Thus, these employees become more valuable to retain and promote because their recommendations have more effect on the organization. Resonance can perpetuate homophily, in a way that looks rationally justifiable, based on performance metrics. Given resonance, many forms of discrimination can become constrained optimal and self-perpetuate.

We now extend the model, by introducing a labor market in which firms promote workers based on their impact on the organization. It generates systematic differences in promotion probabilities across worker types, even with a type-neutral promotion criterion and without preference-based bias.

Consider a labor market with a single firm, consisting of one boss and $n$ employees. The firm's objective is to take an action $X$ that maximizes expected payoffs, given an unknown state of the world $\theta \in \mathbb{R}$. The firm receives signals from employees and updates its beliefs using a resonance-based learning process.

**Information Structure.** Each employee $i$ observes a private signal about a state $z$ for which all agents have flat priors:

$$s_i = z + \xi_i, \quad \xi_i \sim N(0, \sigma_i^2), \tag{8}$$

where $\sigma_i^2$ represents the precision of worker $i$'s information. A richer theory might have a boss learn about the worker's knowledge. But we assume $\sigma_i^2$ is common knowledge for simplicity. Employees truthfully communicate their signals to the boss. A worker with a lower $\sigma_i^2$ transmits more precise, more useful input to their boss.

Each employee belongs to one of two groups, indexed by $\tau_i \in \{a, b\}$. We assume that the distribution of signal precisions within each group is identical.

**Boss's Decision Rule.** The boss seeks to choose an action $x$ that minimizes expected quadratic loss:

$$\mathbb{E}\left[(x - z)^2 \mid I_B\right], \tag{9}$$

where $I_B$ is the boss's information set. Given the signals $s_1, \ldots, s_n$, the boss updates beliefs using a weighted average:

$$\mathbb{E}[z \mid I_B] = \frac{\sum_i w_i s_i}{\sum_i w_i}, \tag{10}$$

where $w_i = \rho_{ib}\sigma_i^{-2}$ represents the resonance-adjusted weight assigned to worker $i$'s signal. As before, that weight depends on information precision $\sigma_i^{-2}$, but also on the social distance through $\rho_{ib}$. For $b$ types, the social distance with the boss is zero and $\rho_{ib} = 1$ if $\tau_i = b$. For $a$ types, there is distance in type space and $\rho_{ib} < 1$ if $\tau_i = a$.

**Promotion Mechanism.** After choosing $x$, the boss promotes one employee to replace them in the next period. Promotion is based on impact, defined as the worker whose signal had the greatest effect on the chosen action:

$$i^* = \arg\max_i \left| \frac{\partial x}{\partial s_i} \right|. \tag{11}$$

Impact criteria are used widely in promotion policies, including academic promotions, which typically consider impact in the form of citation counts and explicit requests to comment on impact in promotion letters.

**Implications for Labor Market Discrimination** Resonance here implies that the boss assigns additional weight to messages that come from workers who share characteristics with the boss. For

those similar workers, their messages receive more weight in belief updating. Since resonance increases the weight placed on past influential messages, workers whose signals were previously more impactful are more likely to be promoted. Over time, this dynamic reinforces the influence of certain types of employees. This happens, even though the promotion policy is type-neutral and no agents have a type preference for promotion.

A key result of the model is that type $b$ workers have a higher probability of promotion than type $a$ workers, even when the two groups have identical signal distributions. Proof in Appendix A.3.

**Proposition 3.** $P(Promotion \mid \tau_i = b) > P(Promotion \mid \tau_i = a)$.

Thus, even in the absence of explicit bias or productivity differences, resonance can generate systematic disparities in promotion rates across worker types by making same-type workers more influential. This suggests a novel mechanism through which structural disadvantage can emerge in the labor market.

This model provides a foundation for understanding how resonance-based updating can create persistent labor market disparities. Unlike traditional models of discrimination, which rely on taste-based preferences or statistical differences, this framework shows that endogenous dynamics in information transmission can lead to persistent inequality.

# 4 Evidence from Occupational Choice

Using the American Community Survey (ACS), we provide a first piece of motivating empirical evidence that people place greater weight on information learned from those within their own communities and this can have aggregate effects. Considering observational evidence of ethnic concentration in certain occupations, we explore whether "information resonance" may be a mechanism driving occupational choice. Here we observe young labor force entrants following their community elders into the same occupations. We see that a young person's choice to enter an occupation is positively correlated with the extent to which people of their same ethnic group are overrepresented in that occupation in their locality. Then, we further test our hypothesis by examining how a negative shock to members of one's community impacts the behavior of the group. Lastly, we test the prediction that the effect on beliefs will be stronger when matching more demographic characteristics. We include an additional measure of social proximity using gender and hypothesize that young members of an ethnic community will enter occupations in which elders of the same ethnicity *and* gender are overrepresented. If men and women of the same ethnic communities have overlapping social networks, these findings can help rule out information access.

This analysis makes progress in isolating resonance from other forces. But it also makes clear the limitations. Aggregate data alone cannot rule out every possible alternative explanation. The

setting is too rich in interconnections. While this section paints a picture of how resonance can operate in an aggregate economy, true identification of resonance is the job of the experiment, presented in Section 1.

**ACS Data and Variables** The micro data, obtained via IPUMS, comes from the US Census Bureau's annual American Community Survey (ACS) years 2005 to 2020. The analysis uses variables on age, occupation, education, migration, and ancestry of respondents. We aggregate 338 unique occupations (including "unemployed") into 33 broader occupation groups. Taking out those who are unemployed, we are left with 32 occupation groups. Ethnicity is measured using respondents' self-reported familial ancestry. From these ancestries, we construct 17 ethnic groups based on global geographic regions, splitting North America into 3 categories based on race, North American (primarily white North American), African American, and Indigenous American. We measure geographic proximity using Public Use Microdata Areas (PUMAs). PUMAs are geographic statistical areas of the United States each containing a population of at least 100,000 people. When considering occupation choices, we focus on individuals at the start of their career, so we restrict our sample to 18-22-year-olds. Since we aim to capture whether or not people learn from their local community, we look only at youth who have not moved out of their PUMA in the last year (since prior data about moving is not available). We also exclude 18-22-year-olds who were currently attending school. This restriction ensures that the young people in our analysis are in the occupations they chose, rather than enrolled in degree programs working towards the occupations they would like.

**Ethnic Overrepresentation** We define Ethnic Overrepresentation (Ethnic ORep) as the extent to which an ethnic group is overrepresented in an occupation within a PUMA. It is computed as the difference between the fraction of workers in an occupation from that ethnic group (Ethnic Ratio) and the overall share of workers in that occupation (Local Ratio).[7]

Let $i$ be an ethnicity, $j$ be an occupation, $k$ be a PUMA, and $t$ be a year, then ethnic overrepresentation is defined as

$$Ethnic\ ORep_{i,j,k,t} = Ethnic\ Ratio_{i,j,k,t} - Local\ Ratio_{j,k,t}.$$

Similarly, we measure the ethnic ratio for the 18–22-year-old cohort, i.e. the fraction of 18-22-year-olds of each ethnic group in each occupation in each PUMA each year (denoted as *Youth Rate*). This variable is defined as

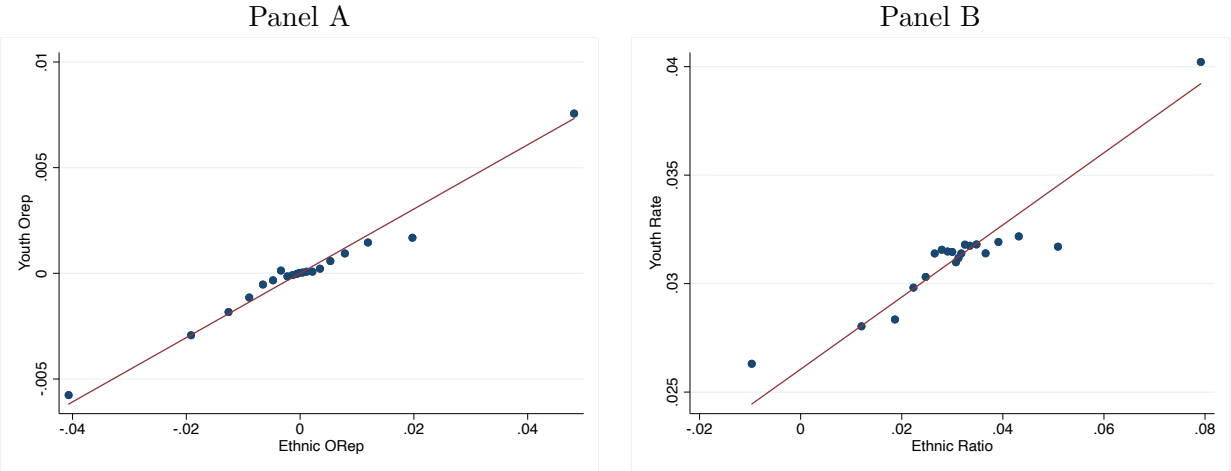
$$Youth\ Rate_{i,j,k,t} = \frac{Occupation\ Size_{i,j,k,t}}{Population\ Size_{i,k,t}}.$$

[7]For a detailed description of how these variables were constructed, see the Appendix-Section C.

*Youth ORep* then refers to the extent to which young adults of a given ethnicity are overrepresented in an occupation relative to their peers.

Looking at simple correlations, we can see a pattern emerge. Figure 3 shows that young labor force entrants are following in the path of their same ethnic elders. In Panel A, we can see that as ethnic overrepresentation increases, youth overrepresentation increases, as well. Panel B shows that the same relationship holds for the level of ethnic concentration in an occupation.

Figure 3: Relationship Between Ethnic Overrespresentation and Youth Entry




***Notes***: Figures include occupation fixed effects and regressions are weighted by the number of young people in the ethnic/occupation/PUMA/year bin. Panel B includes *Local Ratio* as an additional control variable.

Taking this analysis further, we run a linear regression of the youths rate of choosing an occupation within a local-ethnic group, the proportion of 18-to-22-year-olds in each occupation in each PUMA-ethnicity pair each year, on ethnic overrepresentation, the percent amount by which the ethnic group is overrepresented in the occupation in the PUMA that year. Our baseline specification is

$$Youth\ Rate_{i,j,k,t} = \gamma_{j,k,t} + \beta(Ethnic\ ORep_{i,j,k,t}) + \varepsilon_{i,j,k,t},$$

where $\gamma_{j,k,t}$ is an occupation-PUMA-year fixed effect and $\varepsilon$ is the error term. $\beta$ is the coefficient of interest on ethnic overrepresentation and has the interpretation that in a given year for a one percent increase in ethnic overrepresentation, youth choice of that occupation in that puma-ethnicity pair will increase by $\beta$ percentage points.

Table 2 displays the result. Column (6) represents our baseline specification. Here, all location, occupation, and time-specific variation is accounted for, meaning that the remaining variation in occupation choice comes from ethnicity. This allows us to interpret the coefficient on *Ethnic ORep* as the influence of ethnicity on occupation choice holding other local factors constant. If Ethnic ORep increases by 1.2% (the IQR of *Ethnic ORep*), *Youth Rate* will increase by 0.2 pp– 6% of the

mean. Notice that in column (7) of Table 2, the magnitude of the coefficient drops dramatically. Here, all variation in $\beta$ comes from year-over-year changes in *Ethnic ORep*, not the level of ethnic overrepresentation itself. The drop in the coefficient provides further evidence that it is the ethnic concentration in an occupation that matters for youth occupation choice, not only population changes over time.

**Ruling out Information Frictions** In addition to ethnicity, we consider gender as another measure of social proximity. Including gender allows us to disentangle the role of information frictions in occupation choice. Presumably, husbands and wives, fathers and daughters, share information about their jobs and engage in the same social and professional networks. Following same gender elders in addition to same ethnicity elders into occupations rules out information access as the only mechanism driving the pattern.

The variable *Ethnic ORep (Wrong Gender)* is the the degree to which elders of the *same ethnic group* but *other gender* are overrepresented in an occupation.

The Appendix shows that people are following their same ethnicity elders occupational paths within gender. If a given gender of an ethnic group in a PUMA is overrepresented in an occupation by 1.2 percent, the fraction of young people of the same gender-ethnicity going into the occupation will increase by 0.28 pp. If members of the same ethnicity, but opposite gender are overrepresented by the same amount, we reduce the effect by 0.08 pp, showing that people move towards same-gender occupations, but move away from those popular among the opposite gender.

**Economic Shock** Next, we examine how ethnic communities responded to mass layoffs during the Great Recession. Young workers were significantly less likely to enter occupations where their coethnic elders had faced high job losses. This suggests that negative labor market shocks resonate most strongly within socially proximate groups, shaping long-term career choices.

To measure the ethnic-specific effect, we calculate the difference in the number of people in the occupation-PUMA-year in 2006 versus in 2010. We then use the reduction in the number of people employed in an occupation from 2006 to 2010 as a proxy for "layoffs." The variable *High Layoffs* is defined to equal 1 if the percent reduction in employment for an occupation in a PUMA from 2006 to 2010 is in the top 30% across all PUMAs and 0 otherwise.[8] We include an indicator variable, *POST*, indicating that the observation is from the year 2010 or later (i.e., post-recession).

Table 4 shows a positive coefficient on the interaction of the high layoffs dummy and pre-recession ethnic overrepresentation, showing that prior to the recession, young people were following

[8]For this analysis, we fix the ethnic overrepresentation variable to its average of 2005 and 2006. Thus, this variable represents the overrepresentation of the ethnic group in an occupation before the recession. Fixing the variable to a past value allows us to see how young people respond to what they observed *before* making their occupation choice and how those observations impacted their behavior after the recession. Here, we use data from 2005 and 2006 as our "pre-recession" years, and data from 2010 and 11 to study the "post-recession" effects.

their coethnic elders into occupations where they were overrepresented. After the recession, the effect is reversed. Young people are deterred from occupations in which their ethnic community experienced large job losses. Looking at the triple interaction of *High Layoffs* X *POST* X *Ethnic ORep* in column (6), we see that if a job experienced high layoffs during the recession, an ethnic group being overrepresented by 1 percent prior to the recession implies that the fraction of young people entering this occupation will decrease by .2 pp after the recession. Meanwhile, we do not see a significant effect of the recession on occupations that did not experience mass layoffs (the coefficient on *POST* X *Ethnic ORep* is insignificant)– meaning that young people are continuing to follow their same-ethnic elders' career paths in the absence of a shock.

**Identification Challenges** The preceeding empirical results serve as motivating evidence that people place greater weight on information learned from people they are socially close to. However, identification of information resonance poses many questions that this empirical exercise does not address. One challenge of isolating information resonance is that correlated information and selection can mimic each other. People in a community might behave similarly because they have learned from each other and have similar beliefs. Alternatively, they might also select into a community because of similar behavior and preferences, as in models with social norms, or due to their beliefs. Another potential issue is Manski (1993)'s reflection problem: It is difficult to distinguish how an individual affects a group from the group's effect on the individual.[9]

These problems illustrate why it is useful to build a model that captures these compounding effects. They also motivate our use of experimental evidence in Section 1. But even if all these econometric problems are present, none of them negates the finding that people have social influence on others like them, in ways that affect aggregate outcomes.

# 5 Conclusion

This paper explores the difference between information access and information resonance. We note that in the modern world, with abundant data at our fingertips, most people do not lack access to information. Instead, they need information that speaks to them in a meaningful way. Neuroscience research suggests that information affects choices when the observer of that information connects to that information, in an emotional way. Emotional connections with anothers' experience is stronger when the observer and the information provider have similar characteristics. The set of characteristics that trigger resonance appears to be large.

[9]The reflection problem is predominantly an issue with linear-in-means models; however, Brock and Durlauf (2001) highlights how in a backward-looking, dynamic linear-in-means model where current behaviors are driven by past beliefs the reflection problem does not apply. Our model relies centrally on past experiences, therefore it is unlikely that the reflection problem would be exhibited.

By formally modeling this phenomenon, we learn about policies that could be more effective in inducing behavioral change. Having the right people convey public health measure might induce better compliance. One well-placed local leader may be as effective as many, many outsiders and expensive advertising.

Finally, the process of information diffusion governs everything from technological adoption, to political attitudes, to financial trading strategies. It can affect aggregate economic outcomes, like occupational choice.Our experimental evidence shows that this diffusion happens not only in geographic space, but in social characteristic space. This change in focus, from information access to information resonance, could change the way we organize social science data for analysis and the way we enact policy to improve our collective well-being.

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Table 2: Occupation Choice: Ethnicity

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Ethnic ORep | 0.571*** | 0.176*** | 0.175*** | 0.234*** | 0.170*** | 0.180*** | 0.0393*** |
| | (0.0436) | (0.0137) | (0.0137) | (0.0133) | (0.00874) | (0.0106) | (0.0115) |
| Constant | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** |
| | (0.000449) | (0.000124) | (0.000125) | (0.000102) | (0.0000652) | (0.0000813) | (8.24e-20) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No |
| Occupation X Year FE | No | No | Yes | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes |
| Observations | 1203328 | 1203328 | 1203328 | 1203328 | 1202976 | 1050624 | 1196736 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Occupation Choice: Ethnicity, Gender

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Ethnic ORep (Same Gender) | 0.406*** | 0.221*** | 0.221*** | 0.253*** | 0.218*** | 0.230*** | 0.159*** | 0.333*** |
| | (0.0258) | (0.0131) | (0.0131) | (0.0132) | (0.0121) | (0.0139) | (0.0127) | (0.0262) |
| Ethnic ORep (Wrong Gender) | 0.157*** | -0.0636*** | -0.0639*** | -0.0225* | -0.0634*** | -0.0642*** | -0.121*** | 0 |
| | (0.0200) | (0.0129) | (0.0129) | (0.0127) | (0.0117) | (0.0136) | (0.0124) | (.) |
| Constant | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** |
| | (0.000449) | (0.000125) | (0.000125) | (0.000102) | (0.0000653) | (0.0000702) | (5.57e-19) | (5.73e-19) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No | Yes |
| Occupation X Year FE | No | No | Yes | No | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy X Year FE | No | No | No | No | No | No | No | Yes |
| Observations | 2108064 | 2108064 | 2108064 | 2108064 | 2107904 | 2056448 | 2104672 | 1809472 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Impact of a Shock on Occupation Choice (2005/06 and 2010/11 with Ethnic $ORep_{2005}$)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Ethnic ORep (2005) | 0.614*** | 0.139*** | 0.153*** | 0.323*** | 0.147*** | 0.170*** | 0 |
| | (0.0755) | (0.0335) | (0.0338) | (0.0347) | (0.0291) | (0.0316) | (.) |
| POST=1 | 0.000798** | 0.000830** | 0 | 0.000788** | 0.000774** | 0 | 0.000798** |
| | (0.000393) | (0.000346) | (.) | (0.000346) | (0.000359) | (.) | (0.000346) |
| POST=1 X Ethnic ORep (2005) | -0.000996 | -0.0182 | -0.0468 | 0.00929 | 0.00523 | -0.0456 | 0.00557 |
| | (0.0437) | (0.0391) | (0.0396) | (0.0390) | (0.0403) | (0.0414) | (0.0391) |
| High Layoffs=1 | -0.0179*** | 0.00163*** | -0.00000514 | 0.00143*** | 0 | 0 | 0 |
| | (0.000819) | (0.000434) | (0.000425) | (0.000416) | (.) | (.) | (.) |
| High Layoffs=1 X Ethnic ORep (2005) | -0.0360 | 0.249*** | 0.225*** | 0.153** | 0.262*** | 0.229*** | 0 |
| | (0.115) | (0.0664) | (0.0661) | (0.0637) | (0.0559) | (0.0610) | (.) |
| POST=1 X High Layoffs=1 | -0.00354*** | -0.00327*** | 0.000127 | -0.00310*** | -0.00307*** | 0 | -0.00317*** |
| | (0.000590) | (0.000539) | (0.000503) | (0.000537) | (0.000557) | (.) | (0.000538) |
| POST=1 X High Layoffs=1 X Ethnic ORep (2005) | -0.178** | -0.241*** | -0.184** | -0.252*** | -0.259*** | -0.204*** | -0.259*** |
| | (0.0812) | (0.0763) | (0.0743) | (0.0752) | (0.0759) | (0.0789) | (0.0719) |
| Constant | 0.0372*** | 0.0322*** | 0.0326*** | 0.0322*** | 0.0326*** | 0.0323*** | 0.0326*** |
| | (0.000620) | (0.000262) | (0.000194) | (0.000248) | (0.000182) | (0.000136) | (0.000134) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No |
| Occupation X Year FE | No | No | Yes | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes |
| Observations | 275427 | 275427 | 275427 | 275427 | 274986 | 242493 | 273211 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# A Appendix: Proofs

## A.1 Proof of Proposition 1

**Proposition 1.** It requires $\tilde{J}$ neighbors in scenario 2, to have an equal probability of getting the nearest community member to switch to choosing $a_1$ at date $t = 2$, as one local leader in scenario 1, where $\tilde{J}$ solves

$$Q_1\tilde{J} + Q_2\tilde{J}^{1/2} + Q_3$$

where $Q_1 = \omega_n(E[z_0|\mathcal{I}_0] - z_1)$, $Q_3 = \sigma_1^{-2}(E[z_0|\mathcal{I}_0] - \mu_1)$, and $Q_2 = \omega_n/\omega_{ll} \cdot Q_3 - Q_1$.

**Proof of Proposition 1**:
*Probability of switching action in scenario 1:* The community members closest to the local leader have distance 1 on the grid. Therefore, the weight these nearest neighbors put on the local leader's experience is

$$\omega_{ll} = 2 - 2\Phi\left(\chi \cdot 1\right).$$

An agent chooses action 1 at time 2 if $E[z_1|\mathcal{I}_1] > E[z_0|\mathcal{I}_1]$. Using the formula for expectations (2), we can rewrite this inequality. In scenario 1, where the closest community member $i$ gets only one signal about $z_1$ from the local leader, the beliefs about $z_1$ at time 1 are the left side of

$$V[z_1|\mathcal{I}_{i1}]\left(\sigma_1^{-2}\mu_1 + \omega_{ll}(z_1 + \epsilon_{1,ll})\right) > E[z_0|\mathcal{I}_1].$$

According to our belief updating rule, the inverse of the conditional variance is the precision of the prior plus the resonance weight (which includes the precision) on the new information: $V[z_1|\mathcal{I}_{i1}]^{-1} = \sigma_1^{-2} + \omega_{ll}$. We can rearrange the inequality as

$$\omega_{ll}(z_1 + \epsilon_{1,ll}) > (\sigma_1^{-2} + \omega_{ll})E[z_0|\mathcal{I}_1] - \sigma_1^{-2}\mu_1.$$

Since beliefs about $z_0$ are precise, we can approximate $E[z_0|\mathcal{I}_1] \approx E[z_0|\mathcal{I}_0]$. This approximation allows us to ignore the random component in beliefs about the well-known action $z_0$.

The only random variable in this expression is the signal noise $\epsilon_{1,ll} \sim N(0, \sigma_\epsilon^2)$. Therefore, the probability that the expression holds is given is the normal cumulative density (cdf)

$$Pr[a_i = 1] = 1 - \Phi\left(\frac{1}{\omega_{ll}\sigma_\epsilon}\left[(\sigma_1^{-2} + \omega_{ll})E[z_0|\mathcal{I}_1] - \sigma_1^{-2}\mu_1 - \omega_{ll}z_1\right]\right).$$

*Probability of switching action in scenario 2:* The community member closest to the the neighboring community members have a distance $\gamma$ on the grid. Therefore, the weight this nearest neighbor puts on the experience of each neighbor is

$$\omega_n = 2 - 2\Phi\left(\chi\gamma\right).$$

In scenario 2, the closest community member gets $\tilde{J}$ signals about action 1, each with weight $\omega_n$. Note that these neighbors must be in an arc, a semicircle or a circle to be equally distant to the community member. This arrangement is not the same as the linearly spaced locations illustrated in the figures. In this scenario, the closest agent chooses action 1 if the belief about $z_1$ on the left side is greater than the right:

$$V[z_1|\mathcal{I}'_{i1}]\left(\sigma_1^{-2}\mu_1 + \omega_n\sum_{j=1}^{\tilde{J}}(z_1 + \epsilon_{1,j})\right) > E[z_0|\mathcal{I}_1].$$

According to our belief updating rule, the inverse of the conditional variance is the precision of the prior plus the sum of resonance weights on all the new information: $V[z_1|\mathcal{I}_{i1}]^{-1} = \sigma_1^{-2} + \tilde{J}\omega_n$. We can rearrange this as

$$\omega_n \sum_{j=1}^{\tilde{J}} (z_1 + \epsilon_{1,j}) > (\sigma_1^{-2} + \tilde{J}\omega_n) E[z_0|\mathcal{I}_1] - \sigma_1^{-2}\mu_1.$$

The only random variables in this expression are the signal noise $\epsilon_{1,j} \sim N(0, \sigma_\epsilon^2)$. What matters is the sum of these independent normal variables. That sum has standard deviation $\tilde{J}^{1/2}\sigma_\epsilon$. We use the same approximation of $E[z_0|\mathcal{I}_1] \approx E[z_0|\mathcal{I}_0]$ as before. Therefore, the probability that the expression holds is given my the normal cumulative density (cdf):

$$Pr[a_i = 1] = 1 - \Phi\left( \frac{1}{\omega_n \tilde{J}^{1/2}\sigma_\epsilon} \left[ (\sigma_1^{-2} + \tilde{J}\omega_n) E[z_0|\mathcal{I}_0] - \sigma_1^{-2}\mu_1 - \tilde{J}\omega_n z_1 \right] \right).$$

*Finding the number of neighboring signals $\tilde{J}$ that equates the probabilities of switching actions.* The two probabilities are equal if the expressions inside the cdf's are equal. Thus, $\tilde{J}$ solves

$$\frac{1}{\omega_{ll}\sigma_\epsilon} \left[ (\sigma_1^{-2} + \omega_{ll}) E[z_0|\mathcal{I}_0] - \sigma_1^{-2}\mu_1 - \omega_{ll} z_1 \right] = \frac{1}{\omega_n \tilde{J}^{1/2}\sigma_\epsilon} \left[ (\sigma_1^{-2} + \tilde{J}\omega_n) E[z_0|\mathcal{I}_0] - \sigma_1^{-2}\mu_1 - \tilde{J}\omega_n z_1 \right]$$

Simplifying yields the expression in proposition 1.

## A.2 Proof of Proposition 2

**Proposition 2.** Celebrity outcomes have more influence on others' beliefs when agents are geography -constrainted ($\partial E[z_a|\mathcal{I}]/\partial z_{celeb}$ larger).

**Proof of Proposition 2**:
*Step 1:* Derive $\partial E[z_a|\mathcal{I}]/\partial a_{celeb}$ without the geographic constraint.

To form conditional expectations, we use our belief-formation rule (2). When an agent as access to the geographically-unconstrained information set $\mathcal{I}_{it}^U$, with $N_U$ regular observations and 1 observed celebrity action, their beliefs are

$$\begin{aligned} E[z_k|\mathcal{I}_{it}^U] \quad &= Var[z_k|\mathcal{I}_{it}^U] \Big\{ \sigma_k^{-2}\mu_k + \tilde{\psi}_{i,celeb} 1_{a_{celeb,t}=a_k} \omega_{i,celeb} (z_{celeb} + \epsilon_{celeb,t}) \\ &\qquad + \textstyle\sum_{j=1}^{N_U} \sum_{t'=1}^{t} \tilde{\psi}_{ij} 1_{a_{jt}=a_k} \omega_{ij} (z_k + \epsilon_{kit}) \Big\}. \end{aligned} \tag{12}$$

Notice that this is a linear function of the celebrity action payoff, $(z_{celeb} + \epsilon_{celeb,t})$. The partial derivative $\partial E[z_a|\mathcal{I}^U]/\partial a_{celeb}$ is simply the terms that multiply that payoff, namely, $Var[z_k|\mathcal{I}_{it}^U] 1_{a_{celeb,t}=a_k} \omega_{i,celeb}$.

Importantly, the conditional variance term at the start of the partial derivative is given by (**??**). With $N_U$ regular observations and 1 observed celebrity action, the conditional variance of agent $i$'s belief is

$$Var[z_k|\mathcal{I}_{it}^U] = \left( \sigma_k^{-2} + 1_{a_{celeb,t}=a_k} \omega_{i,celeb} \sum_{j=1}^{N_U} \sum_{t'=1}^{t} 1_{a_{jt}=a_k} \omega_{ij} \right)^{-1}$$

*Step 2:* Derive $\partial E[z_a|\mathcal{I}]/\partial a_{celeb}$ with the geographic constraint.

Using the same belief updating rule for an agent who has a geographically-constrained information set $\mathcal{I}_{it}^C$, with $N_C < N_U$ regular observations and 1 observed celebrity action, the belief is still Notice that this is a linear function of the celebrity action payoff, $(z_{celeb} + \epsilon_{celeb,t})$. The partial derivative $\partial E[z_a|\mathcal{I}^C]/\partial a_{celeb}$ is simply the terms that multiply that payoff. In this case, those terms are $Var[z_k|\mathcal{I}_{it}^C]1_{a_{celeb,t}=a_k}\omega_{i,celeb}$. Notice that the latter terms are identical. The only difference in the influence of celebrity actions comes from the conditional variance. For the geographically-constrained agent, that variance is

$$Var[z_k|\mathcal{I}_{it}^C] = \left(\sigma_k^{-2} + 1_{a_{celeb,t}=a_k}\omega_{i,celeb}\sum_{j=1}^{N_C}\sum_{t'=1}^{t} 1_{a_{jt}=a_k}\omega_{ij}\right)^{-1} \tag{13}$$

*Step 3:* Compare $\partial E[z_a|\mathcal{I}]/\partial a_{celeb}$ in both cases.

The partial derivatives in the two cases differ only by their conditional variances. To facilitate comparison, consider the conditional precisions, the inverse of the variances:

$$Var[z_k|\mathcal{I}_{it}^U]^{-1} = \sigma_k^{-2} + 1_{a_{celeb,t}=a_k}\omega_{i,celeb}\sum_{j=1}^{N_U}\sum_{t'=1}^{t} 1_{a_{jt}=a_k}\omega_{ij} \tag{14}$$

We can break the sum of $N^U$ nodes into the $N^C$ nodes that are inside the geographic constraint and the $N^U - N^C$ nodes that are not:

$$Var[z_k|\mathcal{I}_{it}^U]^{-1} = \sigma_k^{-2} + 1_{a_{celeb,t}=a_k}\omega_{i,celeb}\sum_{j=1}^{N_C}\sum_{t'=1}^{t} 1_{a_{jt}=a_k}\omega_{ij} + \sum_{j=N_C+1}^{N_U}\sum_{t'=1}^{t} 1_{a_{jt}=a_k}\omega_{ij} \tag{15}$$

$$Var[z_k|\mathcal{I}_{it}^U]^{-1} = Var[z_k|\mathcal{I}_{it}^C]^{-1} + \sum_{j=N_C+1}^{N_U}\sum_{t'=1}^{t} 1_{a_{jt}=a_k}\omega_{ij} \tag{16}$$

Since the indicator function is non-negative and the weight $\omega_{ij} > 0$, we have $Var[z_k|\mathcal{I}_{it}^U]^{-1} \geq Var[z_k|\mathcal{I}_{it}^C]^{-1}$, with a strict inequality, whenever $\sum_{j=N_C+1}^{N_U}\sum_{t'=1}^{t} 1_{a_{jt}=a_k}$, which means that at least one agent outside the geographic constraint zone took action $k$.

Since $Var[z_k|\mathcal{I}_{it}^U]^{-1} \geq Var[z_k|\mathcal{I}_{it}^C]^{-1}$, $Var[z_k|\mathcal{I}_{it}^U] \leq Var[z_k|\mathcal{I}_{it}^C]$. Since this was the only term that differed between the derivatives and the other terms were positive, $\partial E[z_a|\mathcal{I}^C]/\partial a_{celeb} > \partial E[z_a|\mathcal{I}^U]/\partial a_{celeb}$.

### A.3 Proof: Labor Market Discrimination

The boss updates their belief about the unknown state $\theta$ using signals from workers:

$$s_i = \theta + \xi_i, \quad \xi_i \sim N(0, \sigma_i^2).$$

The boss's posterior belief about $\theta$, given the signals received, follows a weighted average:

$$E[\theta \mid I_j] = \frac{\sum_i w_i s_i}{\sum_i w_i},$$

where the weight $w_i$ is inversely proportional to the worker's signal variance:

$$w_i = \frac{1}{\sigma_i^2}.$$

Under the resonance mechanism, workers whose past signals had a greater impact on the firm's decisions receive increased weight in future decision-making. That is, if worker $i$ has been historically influential, their effective weight is amplified:

$$w_i' = \rho w_i,$$

where $\rho > 1$ is a resonance factor that depends on past impact.

**Impact on the Chosen Action $X$.** The boss chooses an action to minimize expected squared loss:

$$X^* = E[\theta \mid I_j] = \frac{\sum_i w_i' s_i}{\sum_i w_i'}.$$

The impact of worker $i$'s signal on $X^*$ is:

$$\frac{\partial X^*}{\partial s_i} = \frac{w_i'}{\sum_j w_j'}.$$

A worker is **more likely to be promoted** if their signal has the greatest impact, i.e., if $\frac{\partial X^*}{\partial s_i}$ is maximized.

**Type Dependence in Weights.** Workers belong to two types, $a$ and $b$, where:

- **Type** $a$ workers have signal precision $\sigma_a^2$.
- **Type** $b$ workers have signal precision $\sigma_b^2$.
- Initially, suppose $\sigma_a^2 = \sigma_b^2$, so both types have equal baseline weights.

Under the resonance mechanism, suppose type $b$ workers historically received greater weight (due to small early differences or stochastic noise). Then, in the next period:

$$w_b' = \rho_b w_b, \quad w_a' = \rho_a w_a.$$

Since weight accumulation is self-reinforcing ($\rho_b > \rho_a$), type $b$ workers' signals have a larger effect on $X^*$, leading to:

$$\frac{\partial X^*}{\partial s_b} > \frac{\partial X^*}{\partial s_a}.$$

**Promotion Probability.** Since the boss promotes the worker whose signal had the **largest effect on** $X^*$, the probability that a type $b$ worker is promoted is:

$$P(\text{Promotion} \mid \tau_i = b) = P\left(\frac{\partial X^*}{\partial s_b} > \frac{\partial X^*}{\partial s_a}\right).$$

Given that $w_b' > w_a'$, we conclude that the probability of promotion of type $b$ is higher:

$$P(\text{Promotion} \mid \tau_i = b) > P(\text{Promotion} \mid \tau_i = a).$$

# B Simulation Details

There are three sets of simulations in the results section.

## B.1 The Power of Role Models (Figure ??)

The true distributions of the action payoffs are $z_0 \sim N(5, 100)$ with cost 0 for action 0, and $z_1 \sim N(10, 100)$ with cost 1 for action 1. The individual payoff shocks are distributed $\epsilon_{ait} \sim N(0, 100)$ for both actions, independently drawn for actions, agents, and time. Prior beliefs about the payoffs are $z_0 \sim N(3, 10)$ for action 0, meaning that an agent has prior belief that $E[z_0] = 2.5$, with prior variance 10; and $z_1 \sim N(1.5, 10)$ for action 1.

This simulation is run and plotted in characteristic space, not geographic space. The words location and distance here refer to the location in characteristic space and the distance between such characteristic locations.

**Simulation 1**: Every node on the (20 x 20) grid has a type equal to their location. Note that this implies a uniform distribution of characteristics. Social distance is the Euclidean distance between nodes/agents on this characteristic grid.

There is a local leader in the center, who is given a subsidy of $\tau = 5$ to switch actions. This local leader is also more visible than other agents. Instead of $\theta = 0.2$, the local leader has $\theta = 1$. As a result of our parameter choices, everyone in the 20x20 grid starts with action 0, except for one agent in the center (local leader) who chooses action 1.

We simulate 20 periods of choices by every agent. Every agent updates beliefs each period, after observing others' payoffs. Since random payoff shocks matter greatly for the evolution path, we simulate 100 times and record the fraction of simulations that result in action 1 at that location. The plots are a colorbox plot, with only black and white for colors. Black boxes represent action 0. The simulation starts from the 20x20 grid being black, and the 1x20 squares white. We plot the fraction of simulations where action 1 was taken, for each node at $t = 0$, $t = 10$, $t = 20$.

**Simulation 2**: As before, each node's type is represented by their location, and the grid is 20x20. In addition, we leave 5 empty box lengths above the grid and then have a row of 20 boxes (a 1x20 row) lying above the rest of the grid. This row represents the neighboring community. We give the agents in the 1x20 band of neighboring community nodes above the grid a subsidy of 5 to take action 1: $z_1 - c_1 \sim N(6.5, 10)$. These beliefs and payoffs induce them to all choose action 1, while everyone on the 20x20 grid starts by taking action 0 given the parameter choices.

Note that the neighboring community offers more access to information than the local leader in Simulation 1 because there are twenty neighbors for the community to observe, rather than one local leader. We then simulate and let the agents learn from each other, according to the belief formation rule.We plot the same type of black and white colorbox plot as before for $t = 0$, $t = 10$, and $t = 20$.

## B.2 Crisis as a Time of Re-Invention (Figure ??)

Start by assigning every agent to a node on a (20 x 20) grid. This represents their location in characteristic space. In this representation, social distance is the Euclidean distance between nodes/agents. Then, randomly assign each of these nodes to one geographic location on a $20 \times 20$ grid as well.

The parameters we use are: Action 0 has payoff $z_0 = 5$, with cost 0; action 1 has payoff $z_1 = 10$, with cost 1. The individual payoff shocks are distributed $\epsilon_{ait} \sim N(0, 100)$ for both actions, independently drawn for actions, agents and time. Prior beliefs about each of the action payoffs are: Project 0 $N(2.5, 10)$, meaning that an agent has prior belief that $E[z_0] = 2.5$, with prior variance 10. Prior beliefs for action 1 are $z_1 \sim N(0, 10)$. With these parameters, all agents initially choose action 0.

After the initial period, we introduce a negative shock to the payoffs of both actions. We permanently change $z_0$ from 5 to 3, and change $z_1$ from 10 to 8.

Then, we simulate the choices of all agents for 20 periods, 100 times, and plot the average action in periods 0, 5 and 10. For the first five periods, we control the shocks and hold them fixed across simulations to ensure a crisis-like dynamic. After period 5, shocks are drawn independently across simulations to provide a range of possible future paths. The same average outcomes are plotted in geographic space and characteristic space.

### B.3 Digital Social Networks and the Decline of Experts (Figure 2)

In this exercise, there are no choices or payoffs, only agents with geographic locations and characteristics.

Every node should have a 4-tuple of characteristics: 2 geographical coordinates (x and y-axis) and 2 social coordinates, call those coodinates v and w.

Start by placing one node at each vertex in a 20x20 lattice. There should be 400 nodes with x and y coordinates evenly spaced between 1 and 20. For each node, assign a random value to v and w, drawn from a normal distribution: $v \sim N(10, 5)$ independent of $w \sim N(10, 5)$, for each of the 400 nodes. These draws are also independent across nodes.

Then choose one reference node at the center: $(10, 10)$ location means $x = y = 10$. Set this node's social values to $v = w = 10$. That makes the geographically central node socially central as well.

The geographic figure is a color box plot where the color of each node is the euclidean distance between (10,10) and (v,w). So, location is governed by geographic (x,y) and color is determined by social distance v,w.

The 10x10 box in the center of this plot (around boxes 6-15 on both axes) represent the set of community members that an individual can communicate with when they are geographically constrained. The becomes relevant for the results with a digital community.

Next, we take the subset of nodes in that inner 10x10 box and plot them on the 20x20 $(v, w)$ axis. As before, this is a color box grid. There will be lots of empty nodes on this grid. They show up as white space.

A third color box plot, again on the v,w axis, includes all the 400 original nodes, not just the ones in the 10x10 box.

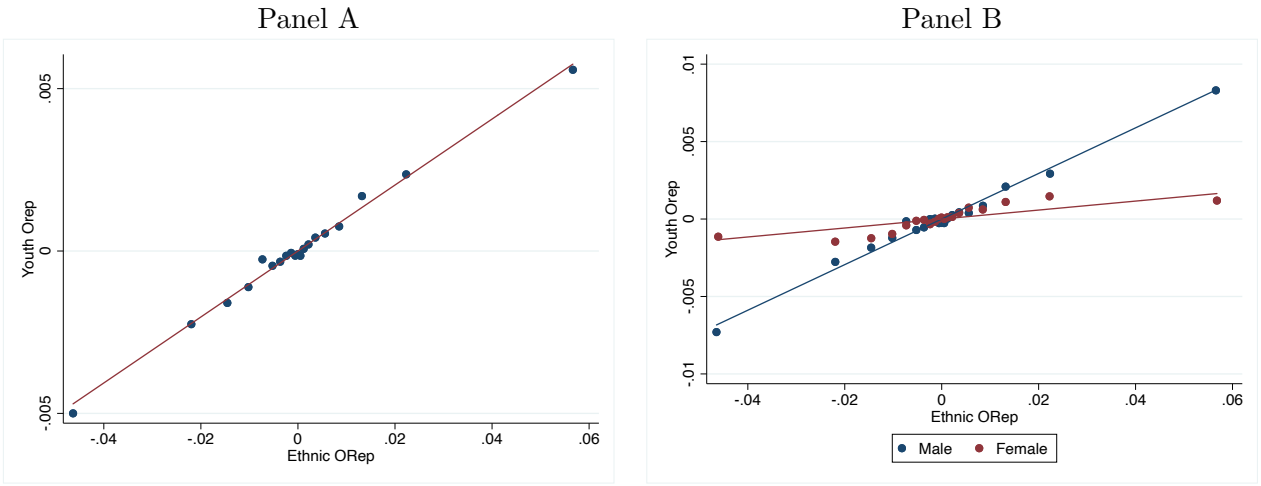
Finally, we repeat the same exercise, but make the central node ($(x, y) = (10, 10)$) have outlier social characteristics. Set $v = w = 2$. This places that node in the minority of the social spectrum.

We construct three more color box plots, following the same procedure as above. Colors now reference the social distance of nodes from the new $(v, w) = (2, 2)$ reference point.

## B.4 Gender-Specific Results

Figure 4 shows the relationship between ethnic-gender overrepresentation and youth entry into occupations. Panel B shows, however, that the relationship is stronger for men, likely due to the weaker attachment of women to the labor force and other cultural factors.

Figure 4: Relationship Between Ethnic Overrespresentation, Youth Entry, and Gender




***Notes***: Figures include occupation fixed effects and and *Ethnic ORep*. Regressions are weighted by the number of young people in the gender/ethnic/occupation/PUMA/year bin.

# C Labor Market Analysis: Data, Variable Construction and Additional Statistics

## C.1 ACS Data and Variables

Micro data was obtained via IPUMS and comes from the US Census Bureau's annual American Community Survey (ACS) years 2005 to 2020. The analysis uses IPUMS variables on age, occupation, education, migration, and ancestry.

IPUMS was formerly an acronym for Integrated Public Use Microdata Series prior to a 2016 change in branding that uses IPUMS name to describe additional projects.

IPUMS variable OCC1990 provides consistent occupation codes across years based on the occupation categorizations from the 1990 decennial census. This variable categorizes 338 unique occupations (including "unemployed"). Using IPUMS's broader categorizations of these occupations, the variable is aggregated into 33 larger occupation groups. Taking out those who are unemployed (since our goal is to measure what occupation a person chooses), we are left with 32 occupation groups on which to do the analysis.

IPUMS variable ANCESTR1 provides the respondent's self-reported ethnic origin and contains 249 unique categories. Removing unknown and other uninterpretable responses,[10] remaining ancestries were grouped into 21 ethnic groups based on global geographic regions as they are defined by the UN Statistical Division and separated North America into three categories based on race, North American (primarily white North American), African American, and Indigenous American. Smaller groups were then combined to create 17 final ethnic groups; South and Central Asia were combined into one region, West Asia and North Africa were combined into "Middle East/North Africa," and Melanesia, Micronesia, and Polynesia were combined into "Pacific Islander."

We include categories "Sub-Saharan African" and "North African" for respondents who identify with African ancestry, however, many Black Americans do not identify with these categories since they've experienced no recent migration in their family. Since ancestry was self-reported, we get the most accurate measure of which community respondents feel most connected to. For instance, even if a Black American has parents from Africa, they may identify more with the Black community in the US than with the African immigrant community. In this case, the respondent would likely choose to identify as "African American" in the survey. This serves our analysis because we want to isolate how people react to the information they receive from groups they identify with.

IPUMS constructed variable CPUMA0010 provides consistent codes for PUMAs across years by matching PUMAs from the 2010 census to corresponding PUMAs from the 2000 census with a 1% mismatch tolerance. Using this variable we were able to identify the PUMA of residence for each individual in the sample across all 15 years of data.

IPUMS variable PERWT provides individual population weights for each person in the sample. This variable describes how many people in the population each particular observation in the sample represents.

IPUMS variable SCHOOL indicates if the respondent was currently attending school. We use this variable to construct a younger cohort of 18–22-year-olds who are not currently attending

[10] Uninterpretable responses include categories that IPUMS has dubbed as "residual," including "mixture," "uncodable," "other," and "not reported," as well as categories that are not descriptive enough to make conculsions about the ethnicity of the respondent ("Eurasian," "Hispanic," "Asian," "Spanish American" and "European, nec)." Removing these observations reduces the number of 26-65 year olds in the sample from 16,516,288 to 16,060,861 and the number of 18-22 year olds in the sample from 417,837 to 405,810.

school. We include this exclusion in order to ensure that the young people in our analysis are in the occupations they chose, rather than enrolled in degree programs working towards the occupations they would like.

IPUMS variable MIGRATE1D provides information on whether and where respondents have moved in the year prior to the survey. We use this variable to maximize the likelihood that the young people in our sample currently live in the place where they grew up. This allows us to capture whether they are learning from those in their communities. Therefore, we look only at 18-22-year-olds who have not moved out of their PUMA in the last year.

## C.2 Constructed Variables

Using a combination of these variables, we measure the fraction of each ethnic group in each occupation in each PUMA each year and construct the variable *Ethnic Ratio*. We do so by taking the number of people of primary working age (which we defined as 26-65) in each of these occupation/ethnic/PUMA/year groups and dividing it by the number of people of the ethnic group in the PUMA in the same year. We weight the estimates appropriately using nationally representative weights provided by IPUMS.

Let $i$ be an ethnic group, $j$ be an occupation, $k$ be a PUMA, and $t$ be a year. Then the number of people in an ethnic/occupation/PUMA/year group is $Occupation\ Size_{i,j,k,t}$ and the total number of people of an ethnic group in a PUMA each year is $Population\ Size_{i,j,k,t}$. Therefore, we have:

$$Ethnic\ Ratio_{i,j,k,t} = \frac{Occupation\ Size_{i,j,k,t}}{Population\ Size_{i,k,t}}$$

All estimates are weighted using the PERWT variable to get the most accurate population estimates of these fractions. Similarly, we construct the variable *Local Ratio* as the fraction of all people in the PUMA in each occupation each year.

$$Local\ Ratio_{j,k,t} = \frac{Occupation\ Size_{j,k,t}}{Population\ Size_{k,t}}$$

*Ethnic ORep* is the difference between *Ethnic Ratio* and *Local Ratio* and it measures the extent to which the ethnic group is overrepresented in an occupation in each PUMA each year.

$$Ethnic\ ORep_{i,j,k,t} = Ethnic\ Ratio_{i,j,k,t} - Local\ Ratio_{j,k,t}$$

Next, we construct the variable *Youth Rate* similarly to *Ethnic Ratio* but for the 18–22-year-old cohort. *Youth Rate* measures the fraction of 18-22-year-olds of each ethnic group in each occupation in each PUMA each year.

$$Youth\ Rate_{i,j,k,t} = \frac{Occupation\ Size_{i,j,k,t}}{Population\ Size_{i,k,t}}$$

We add gender re-estimate the variables *Ethnic Ratio* and *Ethnic ORep* to be gender-specific. Here, *Ethnic Ratio (Same Gender)* measures the fraction of people aged 26-65 of ethnicity $i$ and gender $l$ in occupation $j$ and PUMA $k$ during year $t$.

$$Ethnic\ Ratio\ (Same\ Gender)_{i,l,j,k,t} = \frac{Occupation\ Size_{i,l,j,k,t}}{Population\ Size_{i,l,k,t}}$$

*Ethnic ORep (Same Gender)* now measures the overrepresentation of an ethnic-gender group in an occupation in their PUMA. For instance, how many more Vietnamese women are nail technicians compared to all nail technicians in New York.

$$\textit{Ethnic ORep (Same Gender)}_{i,l,j,k,t} = \textit{Ethnic Ratio (Same Gender)}_{i,l,j,k,t} - \textit{Local Ratio}_{j,l,k,t}$$

We then create *Ethnic ORep (Wrong Gender)*, which is the the degree to which elders of the *same ethnic group* but *opposite gender* are overrepresented in an occupation.

$$\textit{Ethnic ORep (Wrong Gender)}_{i,-l,j,k,t} = \textit{Ethnic Ratio (Wrong Gender)}_{i,-l,j,k,t} - \textit{Local Ratio}_{j,-l,k,t}$$

By including this variable in the regression, we show that young people are not just following the lead of elders of their same ethnicity, but that gender plays an important role as well. This also provides evidence that information access is not the only mechanism at play in determining occupation choices. It is highly likely that people recieve information from community members of both genders, however, we find that they respond to the actions of their same-gender elders.

We construct additional variables for the purpose of analyzing the impact of an economic shock. Using the number of people in each occupation in each PUMA each year, we calculate the difference in the number of people in the occupation in 2006 versus the number of people in the occupation in 2010. We use the reduction in the number of people employed in an occupation from 2006 to 2010 as a proxy for "layoffs." We then construct the variable *High Layoffs*. We take the change in the number of people in the occupation/PUMA from 2006 to 2010 and divide it by the number of people in the occupation/PUMA in 2006, giving the percent reduction in employment for that occupation.

$$\textit{Job Loss}_{j,k} = \textit{Occupation Size}_{j,k,2006} - \textit{Occupation Size}_{j,k,2010}$$

$$\textit{Percent Layoffs}_{j,k} = \frac{\textit{Job Loss}_{j,k}}{\textit{Occupation Size}_{j,k,2006}}$$

The variable *High Layoffs* is then defined to equal 1 if $\textit{Percent Layoffs}_{j,k}$ is in the top 30% and 0 otherwise.

Next, we fix the *Ethnic ORep* variable to $\textit{Ethnic ORep}_{2005}$, which is the average of the *Ethnic ORep* in 2005 and 2006. This variable represents the overrepresentation of the ethnic group in an occupation before the recession. Fixing the variable to a past value allows us to see how young people respond to what they observed *before* making their occupation choice. Using the fixed values, we also run the regression separately for ethnic groups that were overrepresented ($\textit{Ethnic ORep}_{2005}$ was positive) and ethnic groups that were underrepresented ($\textit{Ethnic ORep}_{2005}$ was negative). We see similar results among overrepresented groups, with those who were overrepresented in 2005 turning away from occupations that experienced severe layoffs after the Recession.

### C.3 Labor Market Evidence: Summary Statistics

To construct the baseline estimates of the *Ethnic Ratio* and *Local Ratio* variables, we use the ACS data from 2005 to 2020 including all employed people ages 26 to 65 for which we had occupation and ethnicity information. This data totals 16,060,861 observations. In order to ensure reliable estimates, we required that at least 100 observations of an ethnic group be present in a PUMA in order to include it in the data. With this restriction, one ethnic group, Australians/New Zealanders, drops out of the dataset and we are left with 16 unique ethnicities. We observe a total 1,054 PUMAs

in the data. We observe all 32 occupations for each ethnic group.[11] Table A1 shows the average number of observations of each ethnicity in each occupation/PUMA/year group. Table A2 shows the average number of people in each ethnicity represented by the data. These are the weighted estimates of the number of people in each occupation/PUMA/year group. Tables A3 and A4 provide summary statistics of the constructed variables. Table A3 contains values for the variables dependent on ethnicity only, while Table A4 provides the gender-specific values.

Table A1: Number of Observations of Each Ethnic Group ($Occ\ Size_{i,j,k,t}$ (unweighted))

| Ethnicity | Average | Standard Deviation | 25th Percentile | Median | 75th Percentile | Maximum |
|---|---|---|---|---|---|---|
| Eastern European | 6.11 | 11.15 | 1 | 3 | 7 | 304 |
| Northern European | 9.63 | 25.14 | 1 | 3 | 9 | 1536 |
| Western European | 9.72 | 22.52 | 1 | 4 | 10 | 773 |
| Southern European | 6.82 | 16.69 | 1 | 3 | 7 | 816 |
| Pacific Islander | 6.41 | 10.88 | 0 | 2 | 8 | 81 |
| South Asian | 5.95 | 11.069 | 0 | 2 | 7 | 139 |
| East Asian | 6.33 | 12.74 | 0 | 2 | 7 | 263 |
| Southeast Asian | 6.46 | 12.89 | 0 | 2 | 7 | 233 |
| Middle Eastern/ North African | 5.46 | 8.06 | 0 | 3 | 7 | 56 |
| Latin American/ Caribbean | 7.32 | 19.36 | 0 | 2 | 6 | 392 |
| Central American | 12.67 | 33.50 | 0 | 2 | 11 | 584 |
| South American | 6.41 | 11.78 | 0 | 2 | 7 | 127 |
| North American | 8.33 | 19.40 | 1 | 3 | 8 | 606 |
| Sub-Saharan African | 4.96 | 7.56 | 0 | 2 | 6 | 56 |
| African American | 9.27 | 24.61 | 0 | 2 | 8 | 574 |
| Indigenous American | 6.79 | 13.13 | 0 | 2 | 7 | 186 |

[11] At least one ethnicity is represented in each occupation, however, some ethnicities do not have any members in some occupations. For such ethnicity/occupation pairs the fraction of people in the occupation is equal to zero.

Table A2: Number of People in Each Ethnic Group ($Occ\ Size_{i,j,k,t}$ (weighted))

| Ethnicity | Average | Standard Deviation | 25th Percentile | Median | 75th Percentile | Maximum |
|---|---|---|---|---|---|---|
| Eastern European | 583.41 | 1098.45 | 50 | 236 | 659 | 26336 |
| Northern European | 909.93 | 2394.16 | 77 | 315 | 889 | 145700 |
| Western European | 903.52 | 2063.67 | 75 | 317 | 914 | 69517 |
| Southern European | 689.62 | 1697.21 | 57 | 246 | 719 | 80291 |
| Pacific Islander | 574.54 | 1009.54 | 0 | 146 | 653 | 8289 |
| South Asian | 673.74 | 1273.79 | 0 | 193 | 744 | 17078 |
| East Asian | 639.25 | 1296.60 | 0 | 216 | 681 | 22937 |
| Southeast Asian | 688.45 | 1381.21 | 0 | 240 | 730 | 24692 |
| Middle Eastern/ North African | 619.10 | 944.75 | 0 | 266 | 759.25 | 7147 |
| Latin American/ Caribbean | 989.91 | 2589.06 | 0 | 245 | 863 | 49535 |
| Central American | 1663.67 | 4534.18 | 0 | 287 | 1390 | 89952 |
| South American | 874.75 | 1591.111 | 0 | 246 | 951.25 | 15722 |
| North American | 773.17 | 1823.82 | 38 | 243 | 778 | 56980 |
| Sub-Saharan African | 732.84 | 1194.12 | 0 | 282 | 853 | 11622 |
| African American | 1212.63 | 3218.18 | 0 | 297 | 1057 | 77562 |
| Indigenous American | 594.63 | 1117.05 | 0 | 195.5 | 659.25 | 18394 |

Table A3: Summary of Constructed Variables (Ethnicity)

| | N | Mean | SD | 25th | Median | 75th | Max |
|---|---|---|---|---|---|---|---|
| $Youth\ Rate_{i,j,k,t}$ | 1,203,328 | 0.031 | 0.118 | 0.000 | 0.000 | 0.000 | 1.000 |
| $Youth\ ORep_{i,j,k,t}$ | 1,203,328 | 0.000 | 0.090 | 0.000 | 0.000 | 0.000 | 0.999 |
| $Ethnic\ Ratio_{i,j,k,t}$ | 1,203,328 | 0.031 | 0.046 | 0.003 | 0.014 | 0.039 | 0.566 |
| $Ethnic\ ORep_{i,j,k,t}$ | 1,203,328 | -0.000 | 0.019 | -0.007 | -0.001 | 0.005 | 0.381 |
| $Ethnic\ ORep_{i,j,k,t-1}$ | 1,122,624 | -0.000 | 0.019 | -0.007 | -0.001 | 0.005 | 0.417 |
| $Local\ Ratio_{j,k,t}$ | 1,203,328 | 0.031 | 0.042 | 0.006 | 0.015 | 0.039 | 0.400 |
| $Ethnic\ ORep_{2005}$ | 1,203,328 | -0.000 | 0.017 | -0.005 | -0.000 | 0.004 | 0.337 |
| *Percent Layoffs* | 1,035,800 | -0.172 | 1.176 | -0.277 | -0.004 | 0.220 | 1.000 |
| *Job Loss* | 1,098,528 | -63.336 | 1779.922 | -489.000 | -3.000 | 403.000 | 17714.000 |

Table A4: Summary of Constructed Variables (Ethnicity, Gender)

| | N | Mean | SD | 25th | Median | 75th | Max |
|---|---|---|---|---|---|---|---|
| *Youth Rate*$_{i,l,j,k,t}$ | 2,108,064 | 0.031 | 0.136 | 0.000 | 0.000 | 0.000 | 1.000 |
| *Youth ORep*$_{i,l,j,k,t}$ | 2,108,064 | 0.000 | 0.103 | 0.000 | 0.000 | 0.000 | 0.999 |
| *Ethnic Ratio*$_{i,l,j,k,t}$ | 2,108,064 | 0.031 | 0.054 | 0.000 | 0.009 | 0.037 | 0.652 |
| *Ethnic ORep (Same Gender)*$_{i,l,j,k,t}$ | 2,108,064 | -0.000 | 0.024 | -0.007 | -0.000 | 0.005 | 0.441 |
| *Ethnic ORep (Same Gender)*$_{i,l,j,k,t-1}$ | 1,964,544 | -0.000 | 0.024 | -0.007 | -0.000 | 0.005 | 0.464 |
| *Local Ratio (Same Gender)*$_{i,l,j,k,t}$ | 2,108,064 | 0.031 | 0.048 | 0.003 | 0.012 | 0.038 | 0.560 |
| *Ethnic ORep (Same Gender)*$_{2005}$ | 2,108,064 | -0.000 | 0.020 | -0.005 | -0.000 | 0.004 | 0.389 |
| *Percent Layoffs* | 1,833,188 | -0.170 | 1.149 | -0.274 | -0.004 | 0.218 | 1.000 |
| *Job Loss* | 1,941,440 | -64.108 | 1803.196 | -494.000 | -3.000 | 407.000 | 17714.000 |

Table A5: Occupation Choice: Ethnicity, 1-year Lag

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Ethnic ORep (Lag) | 0.533*** | 0.152*** | 0.151*** | 0.207*** | 0.148*** | 0.156*** | -0.00914 |
| | (0.0445) | (0.0142) | (0.0141) | (0.0139) | (0.00905) | (0.0110) | (0.0123) |
| Constant | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** | 0.0312*** |
| | (0.000454) | (0.000126) | (0.000127) | (0.000104) | (0.0000673) | (0.0000839) | (6.14e-20) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No |
| Occupation X Year FE | No | No | Yes | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes |
| Observations | 1122624 | 1122624 | 1122624 | 1122624 | 1122208 | 978592 | 1115904 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# D Experimental Evidence

# E Evidence on Role Models

Role models, those other feel close to or have resonance with, play a key role in public health campaigns. For example, we saw during the COVID pandemic that famous people recommending vaccines did not work well. The fact that most others had no adverse effects also seemed to have

Table A6: Occupation Choice: Youth Rate on Ethnic Ratio

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Ethnic Ratio | 0.339*** | 0.166*** | 0.166*** | 0.277*** | 0.171*** | 0.180*** | 0.0435*** |
| | (0.0251) | (0.0123) | (0.0123) | (0.0119) | (0.00872) | (0.0106) | (0.0115) |
| Local Ratio | 1.041*** | 0.307*** | 0.280*** | 0.216*** | 0.0969*** | 0 | 0.223*** |
| | (0.0295) | (0.0184) | (0.0187) | (0.0156) | (0.0209) | (.) | (0.0221) |
| Constant | -0.0119*** | 0.0165*** | 0.0173*** | 0.0158*** | 0.0229*** | 0.0256*** | 0.0229*** |
| | (0.000228) | (0.000463) | (0.000481) | (0.000427) | (0.000622) | (0.000332) | (0.000612) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No |
| Occupation X Year FE | No | No | Yes | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes |
| Observations | 1203328 | 1203328 | 1203328 | 1203328 | 1202976 | 1050624 | 1196736 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Occupation Choice: Youth ORep on Ethnic ORep

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Ethnic ORep | 0.148*** | 0.152*** | 0.152*** | 0.133*** | 0.160*** | 0.180*** | 0.0505*** |
| | (0.00751) | (0.00752) | (0.00753) | (0.00790) | (0.00808) | (0.0106) | (0.00911) |
| Constant | 1.14e-19 | 1.10e-19 | 1.10e-19 | 1.10e-19 | 1.10e-19 | 1.29e-19 | 1.12e-19*** |
| | (0.0000657) | (0.0000656) | (0.0000656) | (0.0000587) | (0.0000634) | (0.0000813) | (1.23e-20) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No |
| Occupation X Year FE | No | No | Yes | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes |
| Observations | 1203328 | 1203328 | 1203328 | 1203328 | 1202976 | 1050624 | 1196736 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Impact of a Shock on Occupation Choice (2005/06 and 2010-20)

| | (1) Youth Rate | (2) Youth Rate | (3) Youth Rate | (4) Youth Rate | (5) Youth Rate | (6) Youth Rate | (7) Youth Rate |
|---|---|---|---|---|---|---|---|
| Ethnic ORep (2005) | 0.614*** | 0.143*** | 0.153*** | 0.292*** | 0.146*** | 0.170*** | 0 |
| | (0.0755) | (0.0339) | (0.0338) | (0.0338) | (0.0298) | (0.0315) | (.) |
| POST=1 | 0.000460 | 0.000617** | 0 | 0.000556** | 0.000560** | 0 | 0.000558** |
| | (0.000339) | (0.000275) | (.) | (0.000276) | (0.000277) | (.) | (0.000275) |
| POST=1 X Ethnic ORep (2005) | 0.0204 | 0.0183 | 0.00391 | 0.0480 | 0.0396 | 0.000839 | 0.0433 |
| | (0.0403) | (0.0325) | (0.0328) | (0.0326) | (0.0324) | (0.0337) | (0.0323) |
| High Layoffs=1 | -0.0179*** | 0.00190*** | -0.00000514 | 0.00160*** | 0 | 0 | 0 |
| | (0.000819) | (0.000443) | (0.000425) | (0.000427) | (.) | (.) | (.) |
| High Layoffs=1 X Ethnic ORep (2005) | -0.0360 | 0.249*** | 0.225*** | 0.175*** | 0.270*** | 0.229*** | 0 |
| | (0.115) | (0.0666) | (0.0661) | (0.0643) | (0.0570) | (0.0608) | (.) |
| POST=1 X High Layoffs=1 | -0.00293*** | -0.00246*** | -0.000154 | -0.00221*** | -0.00222*** | 0 | -0.00222*** |
| | (0.000498) | (0.000437) | (0.000413) | (0.000437) | (0.000439) | (.) | (0.000435) |
| POST=1 X High Layoffs=1 X Ethnic ORep (2005) | -0.141* | -0.219*** | -0.185*** | -0.225*** | -0.231*** | -0.178*** | -0.229*** |
| | (0.0741) | (0.0657) | (0.0657) | (0.0647) | (0.0620) | (0.0644) | (0.0618) |
| Constant | 0.0372*** | 0.0321*** | 0.0326*** | 0.0321*** | 0.0325*** | 0.0322*** | 0.0325*** |
| | (0.000620) | (0.000271) | (0.000152) | (0.000261) | (0.000199) | (0.0000937) | (0.000185) |
| Occupation FE | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | No | No | Yes | No | No | Yes | No |
| Occupation X Year FE | No | No | Yes | No | No | No | No |
| Ethnicity FE | No | No | No | Yes | No | No | Yes |
| Occupation X Ethnicity FE | No | No | No | Yes | No | No | No |
| PUMA FE | No | No | No | No | Yes | Yes | Yes |
| Occupation X PUMA FE | No | No | No | No | Yes | No | No |
| Occupation X PUMA X Year FE | No | No | No | No | No | Yes | No |
| Occupation X PUMA X Ethniciy FE | No | No | No | No | No | No | Yes |
| Observations | 829690 | 829690 | 829690 | 829690 | 829580 | 717246 | 829220 |

Clustered standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Categorized Homophily Variables

| **Categories** | **Homophily Variables** |
|---|---|
| Preferences | Prefers a beach (mountain) vacation |
| Preferences | Cat (dog) person |
| Preferences | Likes Coca-Cola (Pepsi) |
| Preferences | Likes (does not like) coffee |
| Preferences | Prefers working from home (the office) |
| Childhood | Had (did not have) a happy childhood |
| Childhood | Was (was not) hospitalized as a child |
| Childhood | Parents divorced or separated (did not divorce or separate) during childhood |
| Childhood | Practiced (did not practice) a sport for at least 5 years growing up |
| Childhood | Collected (did not collect) a set of items as a child |
| Childhood | Broke (did not break) a bone as a child |
| Childhood | Saw (didn't see) most winters growing up |
| Childhood | Played (did not play) a musical instrument for at least 5 years growing up |
| Childhood | Participated (did not participate) in school plays or theater in hs |
| Childhood | Was (was not) allowed to watch TV often as a child |
| Childhood | Went (did not go) to the pool often as a child |
| Demographics | Pro-choice(-life) |
| Demographics | Democrat (Republican) |
| Demographics | From the North (South) of the US |
| Demographics | Man (Woman) |
| Demographics | Religious (not religious) |
| Personality | Has (has not) fired a gun |
| Personality | Extrovert (introvert) |
| Personality | Morning person (night owl) |

little influence. However, having a local leader, like a priest or community doctor, recommend the same action was more effective. NPR reported about the efforts of to "keep an open line of communication with recalcitrant rabbis ... knowing they would have the most influence to convince their followers to get vaccinated," and the ultimate success of this approach: "The rabbis agreed to be vaccinated — and their adherents followed suit" (April 22, 2021). The Australian ABC Network describes how "the knowledge and trust Aboriginal health organizations had with local communities was another reason for Victoria's success" in convincing the Aboriginal population, in particular by "re-framing government messaging for local communities" (August 19, 2021). As for the U.S., the PR Newswire explains, "With the disproportionate impact of the pandemic in

Table A10: Resonance Estimates for Various Homophily Variables.
[no Intercept, Choice Centered at 0]

| | *Dependent variable:* |
|---|---|
| | Homophily Choice |
| Cat (dog) person | 0.247*** |
| | (0.046) |
| Likes (does not like) coffee | 0.126** |
| | (0.049) |
| Extrovert (introvert) | 0.135*** |
| | (0.050) |
| Morning person (night owl) | 0.098* |
| | (0.050) |
| Prefers a beach (mountain) vacation | 0.191*** |
| | (0.047) |
| Likes Coca-Cola (Pepsi) | 0.182*** |
| | (0.051) |
| Democrat (Republican) | 0.341*** |
| | (0.041) |
| From the North (South) of the US | 0.065 |
| | (0.052) |
| Religious (not religious) | 0.222*** |
| | (0.046) |
| Prefers working from home (the office) | 0.026 |
| | (0.052) |
| Man (Woman) | 0.136*** |
| | (0.049) |
| Pro-choice(-life) | 0.170*** |
| | (0.048) |
| Played (did not play) a musical instrument for at least 5 years growing up | 0.092* |
| | (0.050) |
| Was (was not) allowed to watch TV often as a child | 0.096* |
| | (0.050) |
| Went (did not go) to the pool often as a child | 0.139*** |
| | (0.049) |
| Collected (did not collect) a set of items as a child | 0.057 |
| | (0.051) |
| Had (did not have) a happy childhood | 0.000 |
| | (0.052) |
| Saw (didn't see) most winters growing up | 0.120** |
| | (0.049) |
| Broke (did not break) a bone as a child | 0.057 |
| | (0.051) |
| Was (was not) hospitalized as a child | -0.060 |
| | (0.050) |
| Participated (did not participate) in school plays or theater in hs | -0.050 |
| | (0.050) |
| Parents divorced or separated (did not divorce or separate) during childhood | 0.067 |
| | (0.051) |
| Has (has not) fired a gun | 0.140*** |
| | (0.048) |
| Practiced (did not practice) a sport for at least 5 years growing up | 0.086* |
| | (0.050) |
| Observations | 2,305 |
| $R^2$ | 0.078 |
| Adjusted $R^2$ | 0.068 |
| Residual Std. Error | 0.483 (df = 2281) |

rural areas across the country, it's critically important that Americans in rural communities hear these powerful stories from each other, their neighbors" (October 19, 2021). The Villager report that "Union leaders receive COVID-19 vaccine in Harlem, hoping to inspire others to do the same" (February 27, 2021). And the New York Times attributes the narrowed vaccination gap between Black and other racial groups to "decisions made in many states to send familiar faces to knock on doors and dispel myths about the vaccines' effectiveness," such as the case of a store owner and county commissioner in Panola, a small rural town near the Mississippi border, who "led the effort to vaccinate nearly all of her majority Black community," and pro-vaccination campaigns including descendants of participants in the Tuskegee study (October 13, 2021). The campaign successfully eased vaccine hesitancy derived from medical mistrust by positioning community members who had directly suffered from the betrayals of the healthcare industry as trusted informants. The Ad Council noted that "[the descendants] are so perfect to be the storytellers because if they can move past it and see the lessons and drive towards getting people vaccinated, it feels like everyone should be able to do the same."

Story after story spells out how, when local leaders provide resonant information and model pro-vaccination behavior, this influences a segment of the population that had heard, but did not internalize other pro-vaccine information. The effectiveness of information originating from community members is so widely recognized that it shows up as a key strategy in the Center for Disease Control's official Vaccination Field Guide. `www.ccbh.net/wp-content/uploads/2021/09/Field-Guide_CDC_Final_2021.pdf`