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Abstract

Eliciting response is an important first step in social marketing, marketing communications, survey research, and general social solicitations. We investigate which consumer social network characteristics drives their response behavior in contexts ranging from social requests to service interactions. Across 1 exploratory field study and 2 field experiments, we made SMS- and voice-call-based solicitations to 18,000 telecom customers, and used their individual-level mobile metadata to identify and test which social characteristics (e.g., sociability, reciprocity, popularity, status) drove social responsiveness to strangers (likelihood, speed, degree of responsiveness). Basic response latency followed a Poisson distribution. Subjects' social activeness had a positive but inconsistent effect; historical reciprocity had no consistent effect; status related variables (e.g., degree asymmetry, spending, phone model) had consistently strong (negative) effects, which are further qualified by a matching effect based on status homophily. To provide causal evidence, we experimentally manipulated the stranger's perceived social position (using job title and accent), and found a significant interaction: Individuals with lower (higher) social network status responded relatively more to lower (higher) social status strangers. Finally, we discuss new methodological research paradigms for platforms combining verifiable response and social network data, and managerial applications in the era of social agent and social media marketing.

Deciding whether or not to respond to a stranger's request has been a social dilemma throughout human history. The classic biblical parable of the Good Samaritan highlights the inherent trade-offs; although aiding a stranger carries moral imperative, it is costly, and since the stranger harbors unknown-intentions, it is inherently risky[1]. Analogous dilemmas persist in the mobile- and internet- age; responding to faceless, distant strangers is a definitive part and first stage of social interactions on the internet. Responding to strangers is necessary not only for social-agent-based marketing, but is also for political discourse on social media, reputation building on online communities (e.g., interest-based forums, Quora), chat-agents on live-streaming platforms, and weak-tie formation on social networking platforms. In these and many other contexts, customers are often willing to respond to solicitations from strangers despite the risks and costs of fraud[3], commercial spam, and social capacity overload. Understanding the individual-level drivers for such behavior may thus reveal which social forces facilitate or limit social responsiveness, interconnectivity, cooperation, and trust in a world where billions of people are connected through telecommunications and internet platforms, but are disconnected by barriers of psychological distance.

Although we frame and approach these questions from a basic social science perspective, they are directly applicable for social media and influencer marketing, where interactions between brands and consumers are often mediated by an intermediate social agent. In domains ranging from social networking, social media, chat and messaging, and live streaming platforms, brands and firms often employ ostensibly independent social agents to engage, influence, and convert new, potential customers. In contrast with traditional B2C communications, which are more formal and direct, social agents typically employ passive influence strategies, and try to build and leverage social relationships and emotional connections with customers in order to persuade and influence. Furthermore, many social agents are smaller in scale (i.e., not celebrity influencers with millions of followers), which creates more personable interactions and allows for more precise micro-targeting. In such contexts, interactions with social agents are more akin to interpersonal social interactions; subsequently, social interaction norms and dynamics become more important. Our research focus is on what social dynamics drive the first stage of such interactions, where social agents, who are essentially strangers, are trying to elicit basic social response.

Background: Drivers of Social Response

What ultimately determines a person's responsiveness to strangers? For example, if you were trying to solicit a response from a stranger, who would you contact; the most socially active person, the most reciprocal person, the most popular person, or the most high-status person? Although previous literature has shown that each factor can affect social responsiveness toward extant social ties, little is known about their strengths *relative* to each other, particularly during communications with strangers, who are essentially completely unembedded new social ties[a]. In this paper we attempt to understand the relative strength of these factors in predicting mobile responsiveness to strangers by testing them concurrently. Furthermore, in mapping which of these individual-level social characteristics drive individuals' propensity to respond to strangers, we may infer the underlying motivations and social strategies behind their decisions, which aggregate at a macro level to reflect (or shape) the social norms of society[4-8].

We investigated the social characteristics driving response to strangers by combining mobile-phone-based field experiments that elicited real response behavior towards strangers with

[a] In our studies, the stranger is always unambiguously a person who the respondent does not know.

individual-level mobile telecommunications metadata (mobile metadata), which allowed for concurrent multiple hypotheses testing. In addition, we used social psychological experimental manipulations to generate causal tests for the most consistent predictor to emerge, which alleviated endogeneity concerns that would have arisen from a purely predictive model approach that is popular in machine-learning-driven industry research.

Across three field studies, we sent text messages (SMS) or made voice calls to a randomly drawn pool of mobile subscribers in order to generate behavioral dependent variables, i.e., actual social response to a stranger. To identify and test what drove responsiveness to strangers, we matched the subscriber's response (or lack thereof) to 3-months of their own mobile metadata (see Methods), which is commonly used to capture individual social interaction histories and social network structures[9-13, b], which we used to create egocentric variables operationalizing different social characteristics. Since how individuals maintain relationships and treat others not only reflect stable characteristics such as personality, dispositions, and values, but also signal how they approach social interactions within complex social systems[11, 12, 14], one might expect individuals' social characteristics to reflect general interpersonal interaction tendencies, even with strangers.

Our field experiment contexts always involved communications from a stranger, i.e., someone who has no embedded relationships in the respondents' social networks, who is explicitly or implicitly requesting some form of social response (e.g., holiday goodwill, help with a survey, asking for directions). Such requests were not costless, since they require the expenditure of time and effort (and 0.10 Yuan), but are were not overtly risky; for example, we never request personal information. Nonetheless, due to the relatively high incidence and public

[b] Importantly, such data reflects not only in-vitro behavioural tendencies, but also the state of in-vivo social relationships and characteristics.

awareness of telecommunications-based fraud in developing countries such as China[15], respondents were likely wary of potential confidence tricksters when they considered whether or not to respond. When such subjective risks are considered alongside the respondents' psychological distance and anonymity (both of which abet the diffusion of responsibility), any level of response might have been considered surprising. Indeed, response rates likely reflected the relative preponderance of facilitators (e.g., curiosity, goodwill, sociability, trust) versus inhibitors (e.g., laziness, pragmatism, reclusiveness, suspiciousness) of responsiveness amongst our sample population.

Although we are agnostic to the precise psychological motivations behind social responsiveness in our experiments (e.g., sociability versus altruistic concerns), there are conceptual similarities between responding to a stranger's communications request and responding to a strangers' prosocial request[16]. We thus lean upon the psychology and social network literatures for potential conceptual drivers of responsiveness to strangers, which we discuss next. We provide greater detail of our data, measures, and operationalizations in the Methods section.

Social activity. One intuitive hypothesis is that those who have historically been more sociable will also be more socially responsive to communications from strangers. Indeed, prior research has found that sociable people form relatively more new social ties in both face-to-face and online contexts[17-18]. In our dataset, aggregate communications frequency (e.g., total frequency of calls and texts) represents the total level of communications and social activity[11].

Reciprocity. Maintaining one's relationships requires mutual investment and reciprocated social response. Consequently, reciprocity plays a central role in fostering sustainable social behaviors and norms, and is the basic mechanism that binds and upholds individual social networks[19-21]. Social exchange theory predicts that those who reciprocated (i.e., responded) more in past communications should also more likely repeat such actions in the future, even to strangers, because they were most rewarded by such actions[19, 22]. We operationalized historical reciprocity in communications using the ratio of total out- versus in- bound communications; in other words, how much an individual responds for every communications they receive. Although it is possible to construe this measure as people's general tendency to respond in communications, the degree of reciprocity in their behavior, whatever the motivation, still has an important implication for maintaining social and cooperative norms.

Popularity. Popularity and social network size (i.e., degree centrality) reflects sociability, social exposure, and ability to maintain more social relationships. Although previous findings show that higher degree centrality is positively related to adherence of prosocial norms[23-24], it is also less predictive of spontaneous and unplanned acts of helping[23], which our experimental contexts fall under. It is also possible that higher degree centrality reflects social capacity constraints, which we also test. Our analyses considers both degree and out-degree centrality (number of different people the ego has called), which captures how much an individual reaches out to (and needs) others, and historical willingness to create more social ties, which are likely positively correlated with responsiveness to strangers.

Status. Related to individual's popularity is their relative status in a social network. Prior research in evolutionary psychology suggests that higher social network status should correspond with greater pro-sociality, even in one-shot games, since central positions should be occupied by people who most adhere to and benefit from the norm[24-26]. However, social psychological research has also found that high social status individuals are generally less helpful, empathetic, and responsive than their lower social status counterparts because of reduced economic dependence on others and thus less concern of others' social evaluations[27-31]. One possible reason for this disjuncture may be differences in calculation and spontaneity across different social response contexts[5, 8, 23]; a negative social status effect may be stronger in spontaneous contexts such as interactions with strangers. We operationalized status using several proxies, including high-end smartphone ownership, spending, in-degree centrality (number of unique people who have called the ego), which measures how sought after someone is and reflects social resources, power, and social status[14], and degree asymmetry, a new measure we developed reflecting relative imbalance in in-degree versus out-degree centrality, which we define further in Study 1 and Methods.

In social networks, asymmetries and lack of reciprocity in relationships often signify imbalances in relative importance, power, and status between individuals[14, c]. Because social relationships typically do not survive without reciprocation, it takes power imbalances to allow such asymmetries in relationships to persist[19]. For example, celebrities' and influencers' social media accounts on Twitter and Instagram have far more followers than they follow. Since the mobile metadata in each study spans 3 months, significant imbalances in degree asymmetry are likely to be persistent, and unlikely to simply reflect a random fluctuation in incoming versus outgoing communications. One should take care to not confuse this degree asymmetry with reciprocity, which we measure separately; for example, it is possible for a person have very high overall reciprocity by having many reciprocal communications with friends who make up the bulk of their communications, but also have high degree asymmetry because she has many

[c] In our sample of active mobile accounts, there were no individuals who had zero incoming or outgoing communications (so the value of the ratio was never 0 or infinity). However, for robustness, we also added 1 to both the numerator and denominator to avoid problems arising from zero outgoing communications.

contacts who always initiate communications with her and never vice versa (e.g., subordinate always reporting to a superior, and never vice versa).

Strategic Roadmap and Study Summary

Status effects for social response is particularly relevant for social media and influencer marketing. The conventional assumption in social media strategy is that influencers with higher social status (e.g., top influencers, celebrities, bloggers, key opinion leaders, etc.) are more effective at promoting products such as luxury goods. However, we show that this is not necessarily true when eliciting social response, where we find evidence of a matching effect. We find that lower status individuals are more responsive to lower status solicitors and less responsive to higher social status solicitors; likewise, we find higher status individuals are more and less responsive to higher and lower solicitors, respectively. Thus, if marketers want widespread reach in social networks, they are better advised to promote their brand messages via lower-status individuals who other lower-status individuals (the majority of the population; centrality in networks have a power-law distributions). Previous research has also shown that higher status individuals are harder to influence (Aral and Walker 2012), our findings replicate this effect for social status but also show that higher status people are relatively more open and responsive to fellow high status solicitors.

More generally, we investigate the basic question of whether individuals' social characteristics can even predict (and determine) future propensity to respond to strangers; for example, it is possible that those who are more reciprocal to friends may not necessarily be more reciprocal to strangers, or that prior social history is not indicative of social behavior with anonymous strangers. Study 1 sought to map basic response patterns and investigated if, and if so, which individual social characteristics could predict social response to strangers. The relative significance and strength of these factors may also provide insight to what motivates response (and rejection) to communications with strangers. For example, response driven by social activeness, reciprocity, popularity, and status may follow different social mechanisms, which each indicate different motivations and strategies for responding to strangers.

Study 1: Identifying Predictors of Response

We sent one of three standardized text messages to 5,000 randomly selected active mobile phone numbers (alter network = 137,710) during the first three days of the Lunar New Year public holidays[d], and systematically tested which mobile phone metadata derived social characteristics (social activeness, reciprocity, popularity, status) could predict their likelihood of responding to the text message request. We chose this time period as a means to control for busyness and other situational variables (since almost everyone was off work and with their families), and because holiday goodwill and social norms (since many text message greetings were being exchanged) should boost baseline response rates. We used newly purchased mobile phone numbers specially acquired for this study to send the messages. The recipient would have seen a text message from an unknown local number signed off by an unknown stranger[e].

By random assignment, subjects received one of three messages (weighted so that the New Year greeting scenario had fewer respondents). In the New Year greeting scenario (N = 827), the text message contained a New Year greeting, well wishes, and small talk, but no direct request for a response. In the help request scenario (N = 1647), the requester (i.e., the stranger

[d] There is no date effect ($F < 1$), so data for all three days were pooled for analyses.
[e] We signed messages with a highly uncommon but not unusual name to make it clear that the message is not from a friend who recently changed phone numbers. No one responded in a manner that suggests they actually knew someone by this name.

sending the message) ostensibly feels "depressed" with the holidays and asks the recipient to cheer them up with a text message. In the joke sharing context (N = 1690), the requester reports being happy with the holidays, shares a joke, and requests that the recipient reciprocate with an amusing text message (Appendix 3).

We recorded binary response rate (responded: yes or no) as the primary dependent variable. As a robustness check, we also coded responses based on level of detail, and recorded response latency (time elapsed between sending of message and receipt of response), both of which reflect degree of responsiveness. We then linked the response variables with respondents' individual-level mobile metadata (variables in Appendix 1). In all analyses, we included only mobile-to-mobile telecommunications data to filter non-social communications[f], and converted all non-dummy variables into z-scores to facilitate direct comparisons of variables.

Mean response. Telecommunications records showed that 4,164 received the text message; 836 messages never reached the recipient due to service suspension, switched off phones, network overload during the holidays, etc., and were removed from the analysis. Across all scenarios, we received 613 text message responses (response rate = 14.7%). Overall response rates were arguably high considering the anonymity, psychological distance, and costs of responding (effort, time, risk of phishing, 0.10 yuan cost, etc.). Using the New Year greeting scenario as a baseline (14%), we received relatively more responses for the help request (21%), $F = 17.2$ $p < .001$, and fewer responses for the joke request (9%), $F = 14.9$ $p < .001$ (Fig. 1b).

Response latencies were characterized by Poisson distributions; response tended to occur quickly or not at all (Fig. 1), which is consistent with spontaneous motivations for social

[f] We used the carrier's classification variables in the dataset to distinguish commercial, private fixed line, and mobile numbers.

response[8, 23]. Response times also differed by scenario, the help request scenario had the fastest average response, $p < .001$, which may reflect differences in the perceived urgency.

INSERT FIGURE 1 ABOUT HERE

Social characteristics. To test the effect of social activeness, popularity, reciprocity, and status, we first ran logistic regression models (separately for each scenario) that included gender, age, internet data usage[g], and one set of the aforementioned social characteristics as independent variables (Appendix 4), and binary response as the dependent variable. For robustness, we then iteratively ran the competing variables against each other in stepwise logistic regressions (one pair at a time to avoid collinearity). The individual significance of social characteristic variables were consistent across the different analyses (final results in Table 1).

INSERT TABLE 1 ABOUT HERE

Social activeness in text messaging was consistently a positive predictor of response; however, social activeness in calls was consistently a negative predictor. This dichotomy, which we also observed for other variables, may simply reflect that when text and call variables are both in the same model, their coefficients also reflect relative preference or usage propensity for text versus voice based communications (i.e., if people who text more may also call less).

Historical communications reciprocity had a positive effect but was not consistently significant. Reciprocity for calls was a significant positive predictor of response for the greetings

[g] These three independent variables were consistently significant across all models in Study 1.

scenario but not for the other two scenarios, reciprocity for texts was significantly positive in the help condition but not for the other two scenarios.

Out-degree and in-degree centrality were originally intended to operationalize popularity and status, respectively[h], but had similar effects and likely reflected social activeness. Out-degree centrality for texts was a positive predictor in the help and joke sharing scenarios, while in-degree centrality for texts was consistently a significant positive predictor of response. We also found that responders tended to have larger active social networks than non-responders, $M_{response} = 34.2$, $M_{no\ response} = 26.0$, $t(4138) = 9.46$, $p < .001$; thus, people who were more socially active, popular, and busy were more likely to respond. Out-degree and in-degree centrality for calls had negative signs, but this might again reflect telecommunications mode preferences and that people who text (call) more people respond more (less) to text messages.

To overcome the limitations of standard degree centrality variables in capturing status or social power, we created a new variable called degree-asymmetry, which is the relative imbalance of in- versus out-degree centrality; in other words, the ratio of number of different people reaching out to the ego versus the number of different people that the ego reaches out to. Degree asymmetry for texts was the strongest predictor of response across all three scenarios (both in terms of parameter values and statistical significance), and was most robust when competing social network variables were included in the model. Despite conceptual similarities, degree asymmetry seems to be a distinct construct from in-degree centrality since they have opposite signed parameter values (for texts). Importantly, the negative parameter value for degree asymmetry for texts shows it is not merely reflecting communication mode preferences.

[h] Degree centrality was strongly positively correlated with out-degree, so we included only the latter variable to avoid multicollinearity issues. In Table 1, we did not include out-degree centrality due to collinearity with in-degree. All 3 measures were highly inter-correlated, $r = .766 \sim .842$.

Asymmetry, the ratio of people texting versus people texted, also seems to be a distinct construct from historical reciprocity, the ratio of total in versus out-bound texts; they differed in both predictive strength and sign (reciprocity was positive in one scenario).

One interpretation of the negative coefficient of degree asymmetry is that those who are sought after by more social ties than they need to maintain themselves (via self-initiated communications) have more power in a social network, and are less responsive to strangers. This is consistent with previous research showing that higher social status people are less likely to engage in prosocial response[27-31], and that the opposite is the case for lower status individuals who have a greater need to engage with others to obtain socio-economic resources[19].

One might wonder why degree asymmetry for calls was never significant. One possibility is that there is generally more degree balance in calling because it is harder to filter voice calls. When receiving voice calls, respondents can only see the incoming number and have limited time to decide whether or not to pick up (so there is a risk of missing a relevant call). On the other hand, it is far easier to filter text messages since there is more information (message content is visible) and less time pressure. Indeed, mean degree asymmetry for calls was 0.953, while mean degree asymmetry for texts was 0.887. Another possibility is that voice filtering does actually occur, but we are unable to observe it, since the carrier's database only records received calls and does not record rejected calls (e.g., if someone declines a number without picking up) or unanswered calls that did not go to voicemail. Both possibilities could explain why degree asymmetry in voice calls was not a significant predictor.

For the demographic independent variables, the negative coefficient for age could reflect communications mode preferences (e.g., older people may prefer voice calls more); and is also consistent with a social-status effect, since older age is correlated with higher social status. The significantly positive coefficient for male gender in the help scenario may reflect gender differences in risk perception and social norms in responding to strangers[32, 33].

Robustness checks. We conducted several additional analyses using a backward stepwise elimination regression method and obtained robust results. We also obtained the same results after coding only long responses as valid responses (e.g., a long caring message in the help scenario, or an attempt to share a joke in the sharing scenario) and not counting any responses that expressed only curiosity (e.g., “Who is this?”, “Can you explain some more?”); degree asymmetry of text contacts remained the most significant predictor (p’s < .01) of response. Note that degree asymmetry reflects the normalized number of people a person reaches out to and does not measure a baseline propensity for responsiveness, which is captured by the reciprocity measure. Indeed, we find that the negative coefficient for degree asymmetry is larger for more socially active customers (1 standard deviation above versus below median communications frequency).

Overall, Study 1 shows that an individual’s degree asymmetry is the strongest (negative) predictor of their responsiveness to a stranger’s social solicitation, while social activeness and popularity are also significant (but positive) predictors. Reciprocity is the weakest predictor and only significant in one scenario. Nonetheless, the study is limited by its correlational design and cannot test whether degree asymmetry or other factors have a causal impact. Furthermore, although we have provided a conceptual explanation linking degree asymmetry with social status, we have yet to provide experimental evidence of this relationship. We address these limitations in the next two studies, which were designed to reduce endogeneity concerns and to explicitly test the meaning of the constructs, by experimentally manipulating the stranger’s social status.

Study 2: Manipulating Social Position via SMS

To provide a causal test of whether mobile metadata-derived social characteristics affect social response, and whether degree asymmetry reflects social status, Study 2 experimentally manipulated the social status of the requester. Prior research has shown that even though in general higher status people are less helpful, they may become relatively more helpful (e.g., engage in costly indirect reciprocity) when their reputations are at stake[5, 7-8, 34], for example if a high status individual receives a request from another high status individual, who potentially has the power to inflict negative social and reputational consequences in the event of non-cooperative behavior. Finding a significant interaction effect between the requester's social status and the receiver's degree asymmetry would show that degree asymmetry is related to, or at least not independent of social status. In addition, Study 2 cross-validates Study 1 by measuring social response during normal, non-holiday contexts.

We sent text messages to 8000[i] mobile phone numbers (alter network = 191,141; 52% male, M_{age} = 35.6) randomly drawn from the same database as Study 1 (excluding previously selected numbers). The text message was a request from a researcher to participate in a two-question survey (Appendix 5). Participants were randomly assigned to one of two conditions; the only difference between the two conditions was the title of the requester, which was either a high- (Professor and Director) or low-status (student) position. The message was sent by research assistants using six different phone numbers. A reminder message was sent to those who did not reply in the first three days. The dependent variable of interest was a binary response variable of whether individuals answered any of the survey.

[i] Final N = 7997; due to human error by one research assistant, 3 numbers were deleted.

Using the same approach as Study 1, we linked experimental response to respondents' mobile metadata and applied the same logistic regression analysis. We included all previous variables (as z-scores) and added weekend and day-versus-evening dummies to control for busyness, since the study did not take place during a holiday. We also included fixed effects for the individual phone numbers used to send the messages.

Randomization check. Demographics and telecommunications usage were similar in both conditions; there were no significant differences in gender (p = .488), age (p = .519), telecom service tenure (p = 0.989), mobile internet usage (p = .766), and social network size (p = .507).

Mean Response. The student condition received greater response (12.4%) than the professor condition (9.91%), $\chi^2(1, 7997) = 13.6$, $p < .001$. There were no significant differences in customer satisfaction rating (M = 6.87), p = .340, or response time (Median = 20 min; Mean = 278 min), p = .317, in the two conditions.

INSERT TABLE 2 ABOUT HERE

Logistic regression analysis. The status manipulation had a significant main effect in each of the final models: Students (low status) received more response than professors (high status), p = .002. It is possible that the student message elicited greater sympathy since students typically have fewer resources. There was less response during weekends, $p < .001$, suggesting that response probably had less to do with free time availability; it is possible that respondents were relatively less inclined to respond to non-social communications during weekends.

However, time of day was not a significant predictor. Consistent with Study 1, gender was a marginally negative predictor of response ($p = .063$).

Main Effects. The main effects only regression model was consistent with Study 1. Degree asymmetry for text messages was a significant negative predictor of response ($p = .004$), while degree asymmetry for voice calls was a marginally significant positive predictor ($p = .064$). Customers with higher total monthly spending (e.g., telecom services, add-value services, app purchases), which may also reflect socio-economic status, were less responsive ($p < .001$). Reciprocity was not significant (ps > .1) and not included in the final model.

Interaction Effects. We found a significant negative interaction between degree asymmetry for texts and the lower social status dummy ($p = .012$): Customers with higher (lower) degree asymmetry were relatively less likely to respond to the lower status student (higher status professor) requester. There was also a significant negative interaction between monthly spending and the lower status dummy: Customers who spent more were relatively less likely to help the student and more likely to help the professor, $p = .024$. There was no significant interaction between degree asymmetry for calls and lower social status ($p = .303$). The main effects for these variables were subsumed in significance by the interaction terms in Model (B).

Robustness checks. We tested the robustness of degree asymmetry by adding three pairs of competing social characteristics variables into the basic logistic regression model (Appendix 6): Social activeness (communications frequency), in-degree centrality (social demand for a person), and the interaction between in-degree and the status dummy[j]. The positive main effect

[j] Since the three pairs of network variables were highly inter-correlated (r = .612 to .855), we entered one pair of variables at a time into the logistic regression model to avoid collinearity issues

for the status manipulation ($p < .001$) and negative interaction between degree asymmetry for texts and the status manipulation, remained significant in all three robustness check models ($p = .011 \sim .012$). No other variable, including in-degree centrality, had a significant interaction with status.

In addition to replicating Study 1's findings, Study 2 shows that degree asymmetry and social status are non-independent, and that the causal direction of the effect is that social status affects social response. That an alternative proxy for social economic status, monthly spending, also yields a similar interaction effect with the status manipulation, strengthens this interpretation and adds convergent validity. Furthermore, degree asymmetry does not simply reflect a person's communications style or baseline desire to form new social ties; this would not be able to explain the interaction effect, i.e., why high degree asymmetry individuals are more (less) responsive to high (low) status requesters. We continue this line of inquiry in Study 3, which manipulates social status in a different context and communications mode.

Study 3: Manipulating Accents in Voice Calls

Study 3 measured social response in the context of a stranger requesting information (asking for directions) during a live voice call. We manipulated the requester's perceived social status by using different accents of speech, which signal belonging to social groups or regions which may have different levels of social status[35]. The voice-call context of the study has several advantages. Firstly, accent of speech is a more natural manipulation of social status since it is a native component of social interactions (versus announcing one's job title). Secondly, voice-based conversation makes it easier to establish that the requester in Study 3 is asking for help with directions, which makes the motivations and social norms of the interaction less ambiguous relative to Study 1 and 2. Thirdly, Study 3 creates an additional measure of degree of responsiveness based on number of questions answered, which we cross-validated with time spent on the line. Finally, the voice-call context rules out that text-message based degree asymmetry simply reflects how much someone likes to send text messages; this cannot be the case if the variable also predicts response during a voice-call. Again, we expected an interaction effect between accent and degree asymmetry if social status effects are indeed driving response.

2000 mobile phone numbers (alter network = 76,783; 50.7% male, M_{age} = 36) were randomly selected from the same database (stratified so that 34.1% were high-end smartphone users[k], which is an alternative socio-economic status measure), excluding previously used numbers. Research assistants called each respondent and masqueraded as a visitor (i.e., requester) who had ostensibly just arrived in the city and misdialed while trying to call a friend[36], and tries asking for directions "since you are already on the line". The requester then asked ten questions about the most well-known attraction of the city (a centrally located park) that is common knowledge for most local residents (e.g. "Is there a subway line to the park?", "Is it open at night?") (Appendix 7). Questions were asked sequentially so that the respondent could speak as they wished before the next question was asked. The study ended if the respondent answered all ten questions, or if they hung up at any point. Responses were coded on a 1 to 10 interval measure of social response based on the number of questions the respondent answered before hanging up (0 if they hung up without answering any questions). We included a dummy control variable ("no knowledge"; N = 50) for respondents claiming to not know the answers (e.g., because "I'm not from around here."). We also measured duration of phone calls (minutes).

[k] At the time of the study, the carrier classified phones priced over RMB3000 (~US$480; average annual disposable income was ~US$2600) as high-end phones.

We operationalized perceived social status of the requester using speech accent. China is rich in regional accents; individual cities often have their own distinct accent (typically subsets of broader regional/provincial accents). People are likely to be familiar with major regional accents as well as local accents from within their own province. Because of major differences in level of economic development across regions, there are stereotypes of socioeconomic background and status based on accent and place of origin. The geographical hierarchy of Chinese accents is analogous to the U.K., where Received Pronunciation is a prestige dialect, there are distinct accents at the city-level (and sometimes even village-level), and some regional accents can be associated with lower social-class stereotypes[35].

Callers spoke in Putonghua, Beijing, Gansu, or Zigong accents. Putonghua (i.e., Chinese Received Pronunciation) and Beijing (center of political power; one of the richest regions in China) accents are stereotypically associated with higher social status and commonly featured in mass media, and thus easily recognizable. We chose Gansu (a remote and poor province) and Zigong (a smaller city in Sichuan) accents because Chengdu residents are likely to associate the former with distant and underdeveloped provinces, and the latter with less developed small-towns.

Eight research assistants were recruited based on the accuracy of their accents; for consistency, each were assigned to make calls in one accent throughout the experiment (2 callers per accent) and trained to speak a similar manner (e.g., similar friendliness, tone of voice, etc.). To avoid gender interaction effects, all research assistants were male[1]. We used newly purchased mobile phone SIM cards from Beijing (for Putonghua and Beijing conditions), Gansu, and

[1] This avoids creating a damsel in distress scenario that might have introduced other motivations for response.

Zigong so that the displayed area codes would be consistent with the accent. We included fixed effects for each caller and number in our analysis.

Accent manipulation check. We first ran an in-lab manipulation check to test for perceived differences in social status of the accents. Local undergraduates (N = 124) were randomly assigned to listen to an audio recording of the experiment transcript in one of the four accents. The audio recordings were of the same research assistants who conducted Study 3, so participants would have heard the same voice and accents as respondents in the field study. Participants rated the social status, income level, and educational level of the speaker (1 [very low] – 9 [very high]; Appendix 8), which were averaged into a social class measure (Cronbach's $\alpha = .811$). We also measured participants' power, willingness to help the speaker, perceived distance from the speaker, cogency, and liking of accent. Based on their tight clustering (Appendix 9), Putonghua and Beijing accents were pooled to form a "High Status" group, while Gansu and Zigong accents were pooled to form a "Low Status" group. Perceived social class of the High Status group was significantly higher than that of the Low Status group, $M_{high} = 4.85$, $M_{low} = 3.51$, $t(118) = 6.90$ $p < .001$; there were no significant differences within groups (Appendix 10). There were no significant differences in response to Gansu and Zigong accents in the field; this allays concerns that higher response was driven by in-group bias or greater likelihood that the respondent actually knew someone in Zigong (which is also in Sichuan).

Response rate. Of the 2,000 subscribers called, 544 were unreachable (device off, line busy, etc.) and excluded from further analysis. We excluded 108 respondents who picked up and hung up immediately (before the requester had a chance to speak) from the main analysis since they did not receive the experimental treatment (i.e., hear the accent); robustness checks show that results are consistent if we include them. We coded 361 respondents who hung up after listening to at least part of the request as “0” on responsiveness scale since they were cognizant of the request. The other 987 on average answered 2.4 questions and spent 0.95 minutes on line (Figures 2a, 2b).

INSERT FIGURE 2 ABOUT HERE

Regression analysis. We used number of questions asked as the dependent variable in a step-wise linear regression model (Table 3, Appendix 11). The main-effect model (Model A) used the same set of predictors as in Study 1 and 2 with the addition of an accent condition dummy, a high-end smartphone dummy, and fixed effects for each caller. We added degree asymmetry*low status accent and high-end smart-phone* low status accent interaction terms to test if accent interacted with the status-related variables (Model B).

INSERT TABLE 3 ABOUT HERE

Main effects. Model A, which includes only main effects, shows that consistent with previous studies, degree asymmetry, age, high-end smart-phone ownership, and value-added sales (e.g., mobile app purchases), which reflect social economic status, were significant negative predictors of social response (p = .017). On average, lower status accents received more response than higher status accents (p < .001); since the manipulation check shows that requesters with lower status accents sounded meeker, more in need, and less educated or knowledgeable, respondents may have felt that they objectively needed help. This result is analogous with higher response to the 'depressed' requester in Study 1 and the student in Study 2. Reciprocity was never significant (*p*s > .1) and not included in the final model.

Interaction effects. The main effects for degree asymmetry and high end phones were subsumed in significance by their interaction terms with accent (Model B). Degree asymmetry and accent ($p < .001$) and high-end smartphone usage and accent ($p < .001$) both had significant negative interaction effects. In other words, respondents with greater degree asymmetry and respondents wealthy enough to own high-end smartphones (i.e., high status respondents) were relatively more (less) responsive to high (low) status requesters. However, this was by virtue of high status respondents being significantly less responsive to low status accent requests; in absolute terms, high-status respondents were similarly responsive towards high-status accented requesters as low status respondents were.

As a robustness check, we obtained the same main effects and interaction terms when we used the normalized score of number of questions answered and time spent answering questions (Cronbach's $\alpha = 0.91$), which reflects total effort spent in responding, as the dependent variable (Appendix 11).

Discussion

Across five different response-solicitation scenarios, we identified and tested the individual-level social characteristics that could best predict the likelihood, speed, and effort of social response to distant, faceless strangers, with whom the respondent had no prior social interactions. The strongest and most robust drivers were variables relating to social status (degree asymmetry, spending, high-end smartphone ownership), which were consistently negative predictors of response in all studies. Historical social activeness and popularity were inconsistent predictors of social response to strangers; total communications was significant in the 3 scenarios in Study 1, but in- and out- degree centrality were not significant when other centrality variables were entered into the same model. Reciprocity, which is often considered the golden rule of social relations, was consistently not significant, with the exception of the help scenario in Study 1. Taken together, how people historically treated their friends (existing social ties) was not indicative of their propensity to respond to strangers (i.e., unembedded new social ties); relationship norms (reciprocity) and personal disposition (sociability) were overridden by social categorization norms (e.g., a heuristic based on social status) which was the strongest driver of responsiveness to strangers in our experiments.

The most illuminating empirical results were the interaction effects between individuals' social status and the social status manipulation, which show that response dynamics to strangers in the presence of social diversity depends on a form of social status homophily. In other words, who responds more depends on who requester is. For example, we observed that while lower status individuals were generally more responsive to strangers, they were relatively more responsive to low status strangers and less responsive to higher status strangers. The latter effect suggests that lower status individuals were on average not motivated by social hierarchical rules, undiscriminating altruism, or social reward calculation. Nonetheless, while such behavior was discriminatory, it is still consistent with the application of a pro-social norm heuristic of being more responsive when a stranger seems in greater need. Analogously, although higher status individuals were on average less responsive, they discriminated in the opposite direction and were relatively more responsive to other higher status strangers. This might be due to greater caution in social strategy (e.g., because they are more profitable targets of fraud), learned discrimination, or reputation or strategic concerns.

However, understanding the precise psychological motivations underlying these effects is beyond the scope of our current research, and may require research in controlled laboratory environments. Such research may investigate if response to strangers is motivated more by empathy, general openness to strangers, greater need for vigilance, or social reputation concerns[5, 7-8, 27-31, 34]. Our findings suggest that the motivations are likely to differ based on social status interactivity.

Future research may more deeply explore and validate the asymmetry variable. We conceptually defined the variable and experimentally demonstrated that degree asymmetry is related to social status. Although the variable by definition merely a reflection of some social network behavioral propensity, it seems that whatever its causes (e.g., by personality or career choice), the manifestation of persistent imbalance in in- versus out- degree centrality likely reflects differences in status, resources, and/or power[19]. For convergent validity, we showed that social status as operationalized by degree asymmetry, high-end phone model ownership, and spending all had significant interaction effects with experimental manipulations of the social status, which provides evidence of non-independence. Although we are open to alternative interpretations of these variables, any such account needs to explain the interaction effect and why higher (lower) asymmetry individuals are more discriminating against lower (higher) status strangers.

One might note there are some conceptual similarities between social response to strangers and pro-social behavior, particularly in our experimental scenarios involving helping. There may thus be scope for extending our findings to prosocial behavior, where our findings intuit two gaps in the literature. Prior research on pro-social behavior and social status has focused on the impact of the respondent's social status on behaviour[27-31]. However, our findings suggest that the status of the requester of help may also affect the respondent's prosocial intentions in two ways. Firstly we find that lower status respondents are less willing to help higher status requesters; secondly we find that higher status respondents are relatively more willing to help higher status requesters. Investigating analogous phenomena in an explicitly prosocial context may yield insights on why non-cooperative behaviors between social classes exist.

Future research may also seek to extend our findings to different cultural contexts, which might provide opportunities to test how cultural norms affect social response. However, our main effects are consistent with field experiment results from Western countries[27-31], which also find that social status has a negative main effect. Unfortunately, that lower status individuals are expected to shoulder a greater burden of responsibility in maintaining relations with higher status counterparts has been demonstrated to hold true across many diverse cultures[19].

Methodologically, our research shows the value of combining social psychological field experimental manipulations with large consumer-technology databases capturing prior social behavioral history to understand real and meaningful social decisions. This approach sidesteps biases in self-reported survey data, limitations in external validity for in-lab cooperation games and simulations, as well as endogeneity challenges from a purely data-driven approach. Besides creating causal hypothesis tests, the socially contextualized nature of the field experiments allow us to extract meaning from variables that are otherwise de-contextualized in large datasets.

Applications

Given the widespread use of social targeting in industry that leverages individual-level social network data, our research methodology has numerous practical applications. Our results suggest that status dynamics is an important factor for successful social targeting and social response elicitation. For example, in contexts where high or low social status respondents are similarly valuable (e.g., political campaigns or recruiting volunteers), targeting these individuals helps increase the marketing return-on-investment and reduces spam communications. Besides identifying specific social network variables that categorize high versus low status customers, our research suggests that different solicitation strategies should be employed for different customer types. For example, a university endowment donation drive targeting high status alumni may greater response if it is signed by the president instead of say, a current student. Such strategies can potentially be used to overcome disadvantageous selection biases in marketing communications; since despite being more valuable customers, higher status individuals are less likely to respond to solicitations, However, using higher status communicators may backfire for lower social status respondents; for example, university donation requests to younger alumni, who on average have lower social status, may receive higher response if they come from current students on financial aid. Analogously, firms may apply such strategies for service interactions and customer communications.

Overall, we find that people's historical communication patterns do not always reflect how they will respond to communications from new, ambiguous, and unembedded social agents (i.e., complete strangers). Rather, behavioral patterns are most strongly driven by the interaction and matching of social status between the solicitor and solicited person; notably, both high and low social status individuals engage in some form of filtering or 'discrimination'. Although this suggests limits to how responsive people are to strangers when there is social diversity and status is visible[37-38], our experiments actually elicited relatively high average receptivity towards communications from strangers, all things considered. If future research is able to develop a better understanding of the precise motivations behind response for different social status interaction conditions (e.g., if the motivation for low-low is different from low-high status interactions), there may be scope to design social systems, incentives, or norms that reduce barriers, build greater trust, and cooperation in socially diverse environments.

Methods

Data. The telecommunications carrier provided the prior 3 months of data for each customer at the onset of each study. We initially conducted a pilot study allowed us to explore the data and social network variables available on the research platform (Appendix 1-2). All studies, including the pilot, were conducted in Chengdu, Sichuan (population: 18 million, 6th largest city in China), where the carrier provided us with subscribers' demographics (age, gender), spending data (spending on telecommunications, add-value services, phone model price range), and egocentric social network data (Appendix 1), which we used to create different variables reflecting different social characteristic including sociability (e.g., communications frequency, out-degree centrality), popularity (social network size, in-degree centrality), reciprocity (in- divided by out- bound communications frequency), and relative imbalance in in- versus out-bound network size, which we call degree asymmetry.

All studies draw from the same city-wide telecom database, but customers were never resampled. This research focuses on using verifiable data. The telecommunications carrier cross-validates demographic information such as age and gender from national identity databases; all other variables (i.e., mobile metadata) was pulled from the carrier's telecommunications database using standard telecommunications enterprise software.

We included all respondents in our analyses unless they did not receive our response-request, e.g., phone was off, no service, and thus had no opportunity to respond or reject, in which case the carrier reported that our text message or call was not delivered. We report statistics of such cases in each study. All measures and conditions are reported. Anonymized individual-level data pertaining to the results of this research can be made publicly available.

Variables from telecommunications data. We used customer data and ego-centric social network data to infer social characteristics of participants. See Appendix 1 for a summary table of descriptive statistics for each variable.

Communications variables were divided into in-bound versus out-bound, e.g., "Call in frequency" is total number of inbound voice calls made to the customer, "Call out frequency" is total number of outbound voice calls made by the customer. They can be thought of aggregate tie strength measures for directed edges, reflecting total social network activity (for in vs. out).

Variables calculated only using text messages (SMS) or voice calls were labelled as such (e.g., in-degree centrality as calculated by texts or calls only). Variables with no mention of communications mode (i.e., no mention of voice call or text) were calculated using both types of communications.

Basic variables included: Age, Gender (male = 1), High-end smart phone (yes = 1), iPhone user (yes = 1), Monthly payment (¥), Accessible service items, Additional sales items, Value added services, Call out frequency, Call out duration (min), Out-degree Centrality – Calls, Call in frequency, Call in duration (min), In-degree Centrality – Calls, Std. deviation of call duration, Text out frequency, Out-degree Centrality – Texts, Text in frequency, In-degree Centrality – Texts, Reciprocity – Calls, Reciprocity – Texts, Business texts, Business texts unique contacts, Co-degree Centrality – reciprocated contacts by call, Co-degree Centrality – reciprocated contacts by text, Mobile web-use frequency, Mobile web-use duration (min), Mobile web-use volume (kb). We also calculated the following conceptually relevant variables:

Reciprocity. We created a reciprocity measure by dividing total in- and out- bound communications for either SMS or voice-calls. We added 1 to the numerator and denominator to account for cases where there were no out-bound communications.

In- and out- degree centrality. Formally, for a given network G: = (V, E^{-}, E^{+}) with $|V|$ vertices and $|E^{-}|$ incoming edges and $|E^{+}|$ outgoing edges, the in-degree and out-degree centrality of a vertex v is defined as $C_{in}(v) = \sum_{v \in V} E_v^{-}$ and $C_{out}(v) = \sum_{v \in V} E_v^{+}$, respectively.

Degree asymmetry. We created a new variable which we call degree asymmetry, which was a highly significant negative predictor of response in our pilot study. We define the degree asymmetry for vertex v for a given graph G: = (V, E^{-}, E^{+}) as

$$C_{as}(v) = \frac{\sum_{v \in V} E_{v+}^{-} + 1}{\sum_{v \in V} E_v^{+} + 1}$$

This measure captures the relative imbalance of in-degree (-) versus out-degree (+) centrality in a network; in other words, the ratio of number of different people reaching out to the ego versus the number of different people that the ego reaches out to.

Ethical Approval. This research was supported as a Major Program of the National Natural Science Foundation of China and approved by its review committees, as well as the host university's Institutional Review Board. Permission was also given by People's National Congress of Sichuan. In order to capture real response behavior, participants were initially not aware that they were participating in an experiment. Full disclosure and debriefing was given after the experiments (however, not all respondents could be reached in further communications).

The results of our research program have also yielded socially useful results for the government for predicting vulnerability to phishing and fraud in mobile networks.

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Author Contributions

JSJ and JJ conceived the research. JJ and JSJ analysed the data. JSJ wrote the paper. All authors contributed to experiment design, conceptual development, and critical revisions.

Competing Interests

The authors declare no competing interests.

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Figure Legends

Figure 1 | Frequency count of social response in Study 1. (Fig. 1a), response times for each scenario; overall the distribution of response times (median = 26 minutes) reflected that responses tend to occur sooner rather than later. Non-parametric tests showed that response time was faster in the help scenario (median = 13.5 min., 145 responses in first 5 minutes) than the New Year greetings scenario (median = 41 min.), $p < .001$, while share joke (median = 36 min.) and New Year greetings scenarios had similar response times, $p > .5$. 15.4% of people responded within one minute in the help scenario, compared with 5.3% and 0.9% for the share joke and New Year greetings scenarios respectively. (Fig. 1b), overall response rate by scenario, which is highest for the help scenario and lowest for the share joke scenario.

*NB bars denote frequency count so there are no error bars

Figure 2 | Response Rates by Accent in Study 3. (a) Number of questions answered by accent condition. (b) Time spent on line answering questions by accent condition.

TABLE 1: Predictors of response in Study 1 for scenarios A, B, C

Independent Variable	(A) New Year Greetings			(B) Help Request			(C) Joke Sharing		
	Model 1A	Model 2A	Model 3A	Model 1B	Model 2B	Model 3B	Model 1C	Model 2C	Model 3C
Constant	-2.45***	-2.45***	-2.45***	-1.76***	-1.80***	-1.71***	-3.27***	-3.29***	-3.23***
	(0.299)	(0.294)	(0.296)	(0.148)	(0.148)	(0.144)	(0.274)	(0.267)	(0.276)
Gender (Male = 1)	-0.027	-0.075	-0.104	0.309**	0.331**	0.221	0.190	0.194	0.070
	(0.245)	(0.243)	(0.241)	(0.151)	(0.152)	(0.149)	(0.207)	(0.207)	(0.202)
Age	-0.391***	-0.415***	-0.445***	-0.170**	-0.180**	-0.213***	-0.206**	-0.229**	-0.345***
	(0.119)	(0.119)	(0.117)	(0.072)	(0.073)	(0.070)	(0.101)	(0.102)	(0.095)
Web Use	0.086	0.141	0.142	0.226***	0.228***	0.243***	0.026	-0.012	0.019
	(0.124)	(0.120)	(0.120)	(0.066)	(0.066)	(0.066)	(0.102)	(0.104)	(0.094)
Degree Asymmetry (C_{as}) - Calls	-0.143	-0.079	-0.326	-0.009	0.020	0.141	-0.074	-0.021	-0.048
	(0.159)	(0.150)	(0.221)	(0.084)	(0.086)	(0.129)	(0.147)	(0.149)	(0.171)
Degree Asymmetry (C_{as}) - Texts	**-2.10***	**-2.18***	**-2.71***	**-1.28***	**-1.24***	**-2.04***	**-2.20***	**-2.01***	**-2.31***
	(0.542)	(0.535)	(0.789)	(0.230)	(0.228)	(0.376)	(0.479)	(0.469)	(0.490)
Total Calls – Monthly	-0.170			-0.158**			-0.462***		
	(0.134)			(0.079)			(0.141)		
Total Texts– Monthly	0.292**			0.234***			0.261***		
	(0.118)			(0.066)			(0.083)		
In-degree Centrality (C_{in}) - Calls		-0.335*			-0.421***			-0.793***	
		(0.194)			(0.122)			(0.210)	
In-degree Centrality (C_{in}) - Texts		0.209			0.355***			0.481***	
		(0.128)			(0.088)			(0.107)	
Reciprocity - Calls			0.500**			0.246*			-0.104
			(0.252)			(0.139)			(0.232)
Reciprocity - Texts			0.419			0.703**			-0.234
			(0.652)			(0.333)			(0.543)
Sample size	559	559	559	1143	1143	1143	1198	1198	1198

-2 Log Likelihood	444	447	451	1155	1151	1165	679	670	696

*$p \leq .10$, **$p \leq .05$, ***$p \leq .01$ (two-tailed tests); numbers in parentheses are standard errors.

Logistic regressions of Study 1 predicting response rate using recipients' actual telecommunications patterns for the month running up to the experiment dates: independent variables reflect basic usage, social connectivity, degree asymmetry, and demographics. All variables are monthly (i.e., calculated from the month of mobile metadata preceding the experiment).

TABLE 2: Predictors of response with main (A) and interaction (B) effects in Study 2

	(A) Without Interactions		(B) With Interactions	
	B	*Sig.*	*B*	*Sig.*
(Constant)	0.572	<.001	0.206	.343
Low Status	0.228	.002	0.678	.002
Weekend	-2.474	<.001	-2.484	<.001
Male	-0.139	.063	-0.134	.073
Age	-0.056	.139	-0.057	.128
Monthly Payment	-0.155	<.001	-0.061	.290
Degree Asymmetry (C_{as}) -Calls	0.059	.064	0.037	.338
Degree Asymmetry (C_{as}) -Texts	-0.163	**.004**	-0.033	**.683**
Monthly Payment* Low Status			-0.190	.024
Degree Asymmetry (C_{as}) –Calls*Low Status			0.078	.303
Degree Asymmetry (C_{as}) -Texts*Low Status			-0.290	**.012**
Phone Number Fixed Effect	Yes		Yes	
Sample Size	7997		7997	
-2 Log Likelihood	5105		5094	

Regression analysis in Study 2. Model (A) included only main effects without interactions, and (B) included interaction terms. Main effects in (A) show that higher social status respondents are less responsive, but that lower status requesters (i.e., students) generally receive more help. Significant interactions in (B) show that higher status individuals (measured by degree asymmetry-texts and monthly payment) are less likely to respond to lower status requesters and relatively more likely to help high status requesters (i.e., professor). The negative effect of weekend, may suggest that respondents were less responsive during the weekend, or perhaps less willing to reply due to their leisure time mode. However, time of day (day versus evening), (which may be a proxy for situationally-induced mood) were not significant predictors of social response.

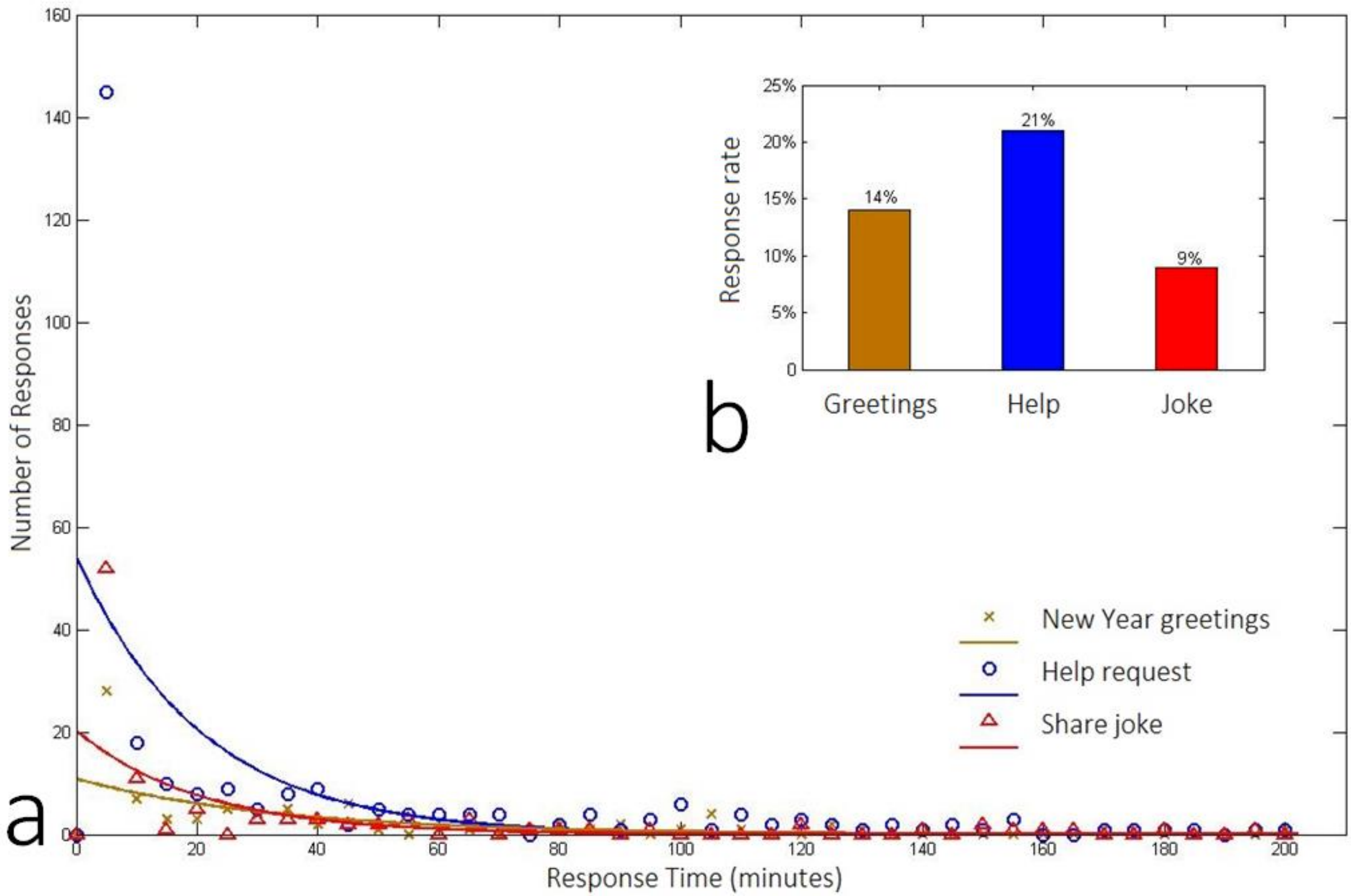
TABLE 3: Predictors of response with main (A) and interaction (B) effects in Study 3

	(A) Without Interactions		(B) With Interactions	
	Beta	*Sig.*	*Beta*	*Sig.*
(Constant)		<.001		<.001
Low Status Accent	0.165	<.001	0.366	<.001
No Knowledge	-0.160	<.001	-0.166	<.001
Age	-0.064	.032	-0.066	.027
Number of Value Added Services	-0.071	.017	-0.069	.019
High-end Smartphone	-0.086	.004		
High-end Smartphone*Low Status Accent			-0.115	<.001
Degree Asymmetry (C_{as}) -Texts	-0.076	.010		
Degree Asymmetry (C_{as}) -Texts*Low Status Accent			-0.174	<.001
Caller fixed effect	Yes		Yes	
Sample Size	1,026		1,026	
F-value	17.87		18.82	
Adj. ***R*** Square	0.129		0.135	

The dependent variable is the number of questions answered in the field experiment.

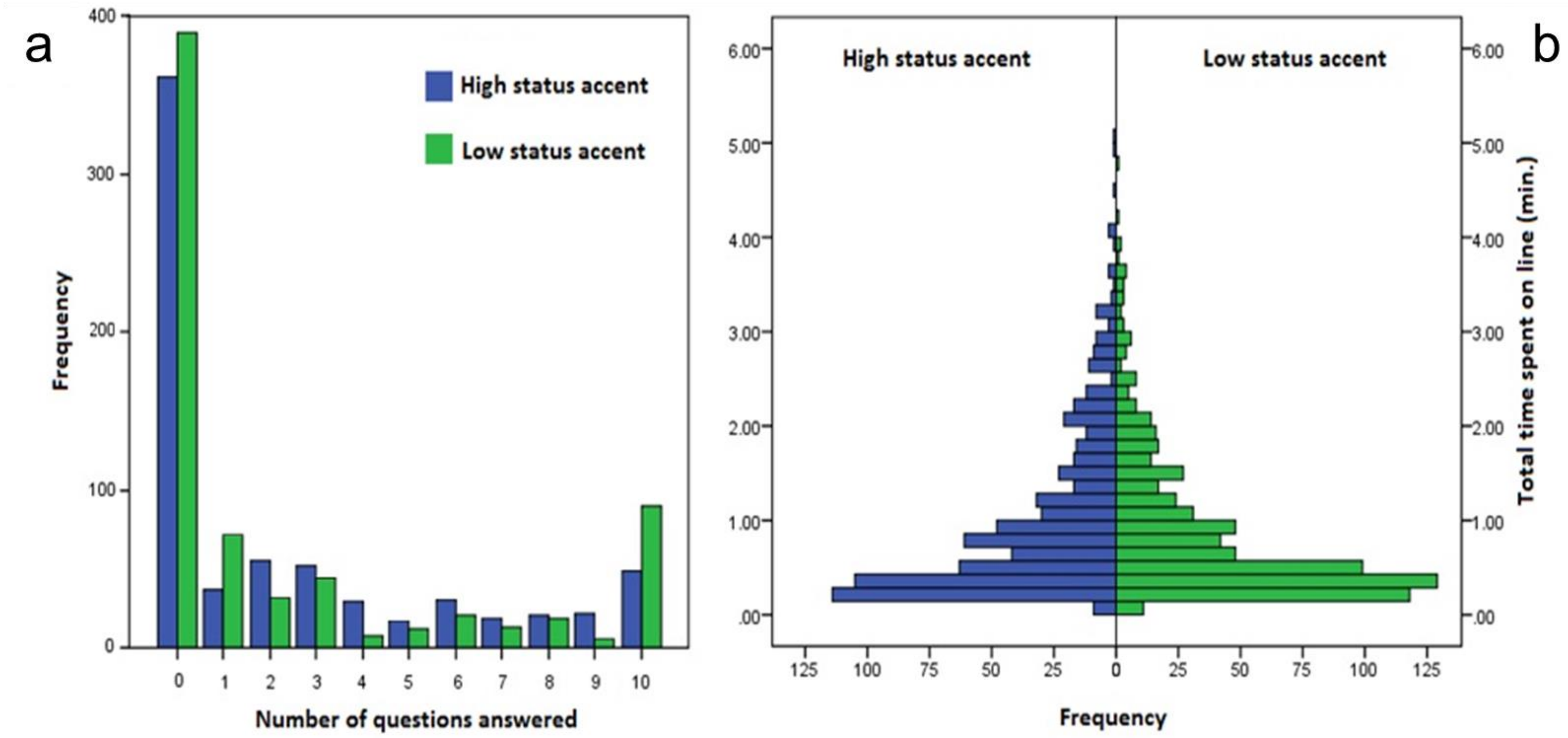
Regressions models in Study 3. Main effects in (A) show that, consistent with Study 2, higher social status respondents are less responsive, but that lower status requesters generally receive more help. Significant interactions in (B) show that higher status individuals are less likely to respond to requesters with lower status accents and relatively more likely to help requesters with higher status accents. The negative effect of weekend, may suggest that respondents were less responsive during the weekend, or perhaps less willing to answer during their leisure time. However, time of day (day versus evening), and weather (raining or not, which may be a proxy for situationally-induced mood) were not significant predictors of social response.

FIGURE 1



160
140
120
100
80
60
40
20
0
Number of Responses
0
20
40
60
80
100
120
140
160
180
200
Response Time (minutes)
a
b
25%
20%
15%
10%
5%
0
Response rate
14%
21%
9%
Greetings
Help
Joke
New Year greetings
Help request
Share joke

FIGURE 2


a
400
300
200
100
0
Frequency
High status accent
Low status accent
0
1
2
3
4
5
6
7
8
9
10
Number of questions answered
b
High status accent
Low status accent
6.00
5.00
4.00
3.00
2.00
1.00
.00
125
100
75
50
25
0
25
50
75
100
125
Frequency
Total time spent on line (min.)

Web Appendix

Appendix 1: Descriptive Statistics of Mobile Network Variables in Pilot Study

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Age	3000	16	60	35.38	9.40
Gender (male = 1)	3000	0	1	53.63%	0.50
High-end smart phone (yes = 1)	3000	0	1	40.00%	0.49
iPhone user (yes = 1)	3000	0	1	32.57%	0.47
Monthly payment (¥)	3000	0	879.65	77.14	76.30
Accessible service items	3000	3	17.67	9.11	1.62
Additional sales items	3000	1	16.00	5.70	2.71
Value added services	2483	0	963.67	22.14	45.60
Call out frequency	2976	0	2948.00	147.47	150.81
Call out duration (min)	2976	0	5354.67	324.08	321.31
Out-degree Centrality - Calls	2976	0	1991.00	39.15	57.65
Call in frequency	2970	0	1688.00	146.96	138.43
Call in duration (min)	2970	0	2786.33	313.63	277.70
In-degree Centrality - Calls	2970	0	510.67	41.07	38.38
Std. deviation of call duration	2976	0	36.72	2.88	2.39
Text out frequency	2958	0	2077.00	84.11	117.77
Out-degree Centrality - Texts	2958	0	620.00	15.52	21.62
Text in frequency	2978	0	2428.00	86.55	116.78
In-degree Centrality - Texts	2978	0	163.33	17.49	14.77
Business texts	2975	0	3681.67	102.33	113.61
Business texts unique contacts	2980	0	89.33	13.74	9.25
Mobile web-use frequency	2518	0	4057.00	421.83	638.80
Mobile web-use duration (min)	2518	0	44600.67	10329.49	13186.89
Mobile web-use volume (kb)	2523	0	8224041	230725.29	489646.98
Sample Size	2146				

Here we present descriptive statistics for independent variables we entered into the regression model of the pilot, and also entered into the model testing of later analyses in Studies 1-3. Above statistics are from a pilot sample of 3000 customers randomly drawn from the city-wide database of active users. The randomized draw was stratified so that there would be a higher proportion of high-end phone model users. This was done to facilitate the use of phone model as an alternative operationalization of status. The 3000 customers here were connected with a further 116,500 other people through previous telecommunications. Note that degree asymmetry and asymmetry in communications frequency (i.e., reciprocity measures) are calculated from the above variables and are thus not separately reported.

Appendix 2: Pilot Study

The pilot was a telephone survey of respondents' self-reported level of social helpfulness, which can be thought of as a strong form of social response, which we linked to respondents' individual-level customer records and mobile metadata. We called 3000 randomly selected active subscribers in the carrier's network (who were connected with 116,500 other mobile subscribers in the previous month): 764 participated in the survey; 1222 declined to participate or hung up, and 1014 were unreachable (e.g., phone switched off, no pickup, no service, etc.) and were thus removed from analysis.

We asked participants how much they had previously engaged in three forms of pro-social behaviour in the previous year (public service, charitable donations, recycling) and their predicted willingness to help others in four contexts (willingness to comfort a stranger, willingness to provide directions, willingness to escort a wounded stranger to hospital, general willingness to help), which we normalized to create an index measure of social helpfulness (Cronbach's $\alpha = 0.658$).

We conducted the pilot as an exploratory study to identify potential variables of interest. We entered all variables from Appendix 1 into a linear regression using a step-wise approach to predict social helpfulness. Three variables were significant predictors of social helpfulness (Appendix 2). Average monthly payment for mobile telecommunications services, which reflects total usage of voice call, SMS, and internet services, was a significant positive predictor ($p < .001$). By themselves, in- and out- degree centrality (which we calculated for calls and texts as separate variables) were not significant predictors. However, degree asymmetry for texts, the ratio of in-degree to out-degree centrality for text messages (i.e., number of people trying to reach a respondent relative to number of people the respondent is trying to reach, by SMS) was a significant negative predictor ($p = .019$). The dummy for iPhone ownership[m] was also a significant negative predictor ($p = .038$).

Subscribers' mobile phone's price-category can be thought of as an alternative operationalization for status. Since subscribers in the Chinese market typically buy mobile phones at unsubsidized prices separately from phone plans, the price is some reflection of discretionary spending power and social economic status. For example, iPhone ownership, which is a significant negative coefficient of helpfulness, may reflect high social economic status since the price of a new iPhone was 30% of the annual per capita disposable income in urban China at the time of the study.

Inter-correlations for degree centrality variables, In-degree for calls, in-degree for texts, out-degree for calls, and out-degree for texts were all significantly positively correlated with each other. Degree asymmetry for texts was negatively correlated with in-degree for texts, out-degree for texts, and degree asymmetry for calls, and was not significantly correlated with in- and out-degree for calls. Degree asymmetry for calls was negatively correlated with out-degree centrality for calls, but was positively correlated with all other centrality variables.

[m] Sampling was stratified so that roughly 1/3 subscribers contacted were iPhone users.

	Beta	Sig.
(Constant)		.320
Monthly Usage of Mobile Services	0.202	<.001
Degree Asymmetry (C_{as}) - Texts	-0.110	.019
iPhone User (yes = 1)	-0.101	.038
Sample Size		442
F-value		8.68
Adj. ***R*** Square		.050

Individuals' activity in the network (i.e., sociability) is a positive predictor, while degree asymmetry and iPhone usage are negative predictors of self-reported helpfulness.

Appendix 3: Text Messages used in Study 1 (Translated from Chinese)

Scenario 1: New Year Greetings

It's been a while, first off happy New Year! Buddy*, how's it been? 2012 is here, and you're still irreverent. As you know, all New Year greetings are the same, but I'm not too worried about wasting a few cents to keep in touch. My well wishes are as follows, hold on…… don't see it? I'm done already! Hahaha ~~~
*a gender neutral term was used

Scenario 2: Help Request

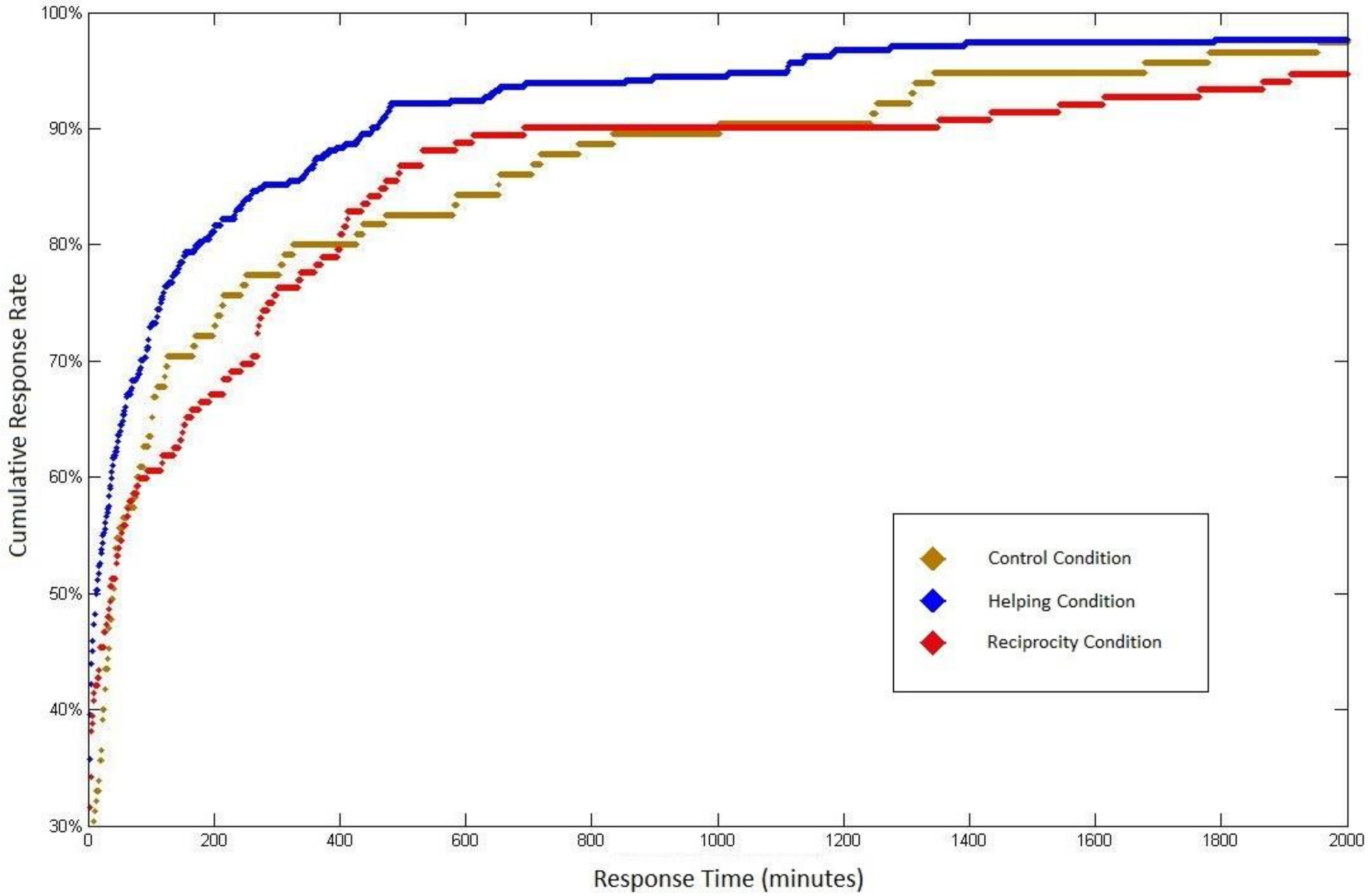
I'm really depressed with the New Year holidays this year. Have you received any fun text messages? Can you send me one to cheer me up a little? Thanks! Happy New Year and best of luck!

Scenario 3: Share Joke Request

I'm really happy with the New Year holidays this year. I've received quite a few fun text messages, and want to share one with you: "The dog said to the bear: Come on, marry me. Marry me and you'll be happy. The bear said: No way, if I marry you we'll give birth to dog-bears. I'm going to marry a cat – giving birth to pandas* is more respectable!" Have you got any fun text messages? Could you send one to me? Thanks! Happy New Year and best of luck!

*The joke is a Chinese pun – the writing for "panda" is comprised of two characters that individually are the characters for "bear" and "cat". The joke was chosen because the authors considered the joke to be funny (or amusingly bad) enough to amuse the recipient, but not so funny that a recipient would feel that any reciprocal joke would be disappointing by comparison

Cumulative response rates for each scenario in Study 1.



Cumulative response time curves reflect how much time it took for the Y% of recipients who eventually responded, to respond. The steeper curve for the helping condition reflects faster overall response times.

Appendix 4: Exploratory Analysis of Centrality Variables in Study 1

Independent Variable	(A) New Year Greetings			(B) Help Request			(C) Joke Sharing		
	Model 1A	Model 2A	Model 3A	Model 1B	Model 2B	Model 3B	Model 1C	Model 2C	Model 3C
Constant	-2.43***	-1.71***	-1.79***	-1.70***	-1.44***	-1.56***	-3.22***	-2.56***	-2.67***
	(0.297)	(0.183)	(0.183)	(0.146)	(0.120)	(0.124)	(0.276)	(0.169)	(0.173)
Male	-0.124	-0.124	-0.134	0.220	0.296**	0.349**	0.072	0.134	0.163
	(0.245)	(0.235)	(0.234)	(0.148)	(0.148)	(0.148)	(0.202)	(0.204)	(0.205)
Age	-0.448***	-0.466***	-0.449***	-0.223***	-0.234***	-0.225**	-0.343**	-0.305**	-0.267***
	(0.119)	(0.115)	(0.114)	(0.070)	(0.070)	(0.070)	(0.095)	(0.100)	(0.100)
Web Use	0.161	0.155	0.189*	0.240***	0.155***	0.271***	0.020	0.031	0.036
	(0.124)	(0.112)	(0.111)	(0.065)	(0.065)	(0.065)	(0.094)	(0.099)	(0.098)
Degree Asymmetry (C_{as}) - Calls	-0.044			0.041			< 0.001		
	(0.147)			(0.080)			(0.139)		
Degree Asymmetry (C_{as}) - Texts	**-2.33*** **			**-1.44*** **			**-2.50*** **		
	(0.534)			(0.228)			(0.480)		
Out-degree Centrality (C_{out}) - Calls		-0.364*			-0.407***			-0.709***	
		(0.193)			(0.125)			(0.196)	
Out-degree Centrality (C_{out}) - Texts		0.370			0.482***			0.570***	
		(0.103)			(0.072)			(0.082)	
In-degree Centrality (C_{in}) - Calls			-0.372			-0.513***			-0.876***
			(0.186)			(0.122)			(0.205)
In-degree Centrality (C_{in}) - Texts			0.399***			0.552***			0.691***
			(0.118)			(0.084)			(0.103)
Sample Size	559	559	559	1143	1143	1143	1198	1198	1198
-2 Log Likelihood	451.3	485.9	480.1	1170	1224	1197	699	713	704

*$p \le .10$, **$p \le .05$, ***$p \le .01$ (two-tailed tests); numbers in parentheses are standard errors; all non-dummy variables are z-scores

Appendix 5: SMS Text for Study 2

In Study 2, subscribers received the following SMS (text) message, which was a request for participation in an academic research survey (done on behalf o the telecom carrier) ostensibly sent by either a student or a professor/institute director (condition determined by random assignment) from a well-known local university.

There is an important reason why the request was said to be from an academic institution conducting market research on behalf of the telecommunications carrier, rather than directly from the carrier. If the request were from the carrier, and sent by an operator or a manager, then response might be motivated by perceived instrumentality of communications; for example, customers with service complaints might believe a manager at the company has more power to address and solve their problems. By saying the message is from an academic research institution, which can confer social status but has little power to affect company policy, we can more cleanly test the impact of the requester's social status.

Message:

Dear Telecom Customer, I am Professor He Jianming, the Director ["I am He Jianming, a student] at X University's Business Research Centre. I would appreciate your help in answering two survey questions; this is very important for my research work.

1. Using a 1 to 10 scale [where 1 is lowest and 10 is highest], how satisfied are you with your telecommunications service?
2. Do you have any recommendations regarding your telecom service?

Please use text message to reply.

[Question 2 was intentionally left open ended. A reminder message was sent to those who did not respond within 3 days. Responses were counted at the end of the week.]

Appendix 6: Robustness Check for Study 2 Using Other Telecommunication Variables

Independent Variable	Model 1	Model 2	Model 3
Constant	0.094	0.022	0.025
	(0.185)	(0.187)	(0.187)
Low Status	0.682***	0.750***	0.746***
	(0.219)	(0.221)	(0.222)
Weekend	-2.483***	-2.484***	-2.486***
	(0.128)	(0.129)	(0.129)
Male	-0.115	-0.081	-0.081
	(0.075)	(0.076)	(0.076)
Age	-0.043	-0.044	-0.043
	(0.038)	(0.038)	(0.038)
Monthly Payment	0.030	-0.072	-0.076

	(0.063)	(0.059)	(0.063)
Degree Asymmetry (Cas) -Calls	0.038	0.092*	0.087*
	(0.043)	(0.048)	(0.049)
Degree Asymmetry (*Cas*) -Texts	-0.038	-0.029	-0.029
	(0.071)	(0.070)	(0.070)
Monthly Payment* Low Status	-0.185**	-0.167**	-0.158
	(0.083)	(0.083)	(0.091)
Degree Asymmetry (C_{as}) –Calls*Low Status	0.077	0.018	0.027
	(0.076)	(0.079)	(0.083)
Degree Asymmetry (C_{as}) -Texts*Low Status	**-0.297****	**-0.293****	**-0.295****
	(0.117)	(0.117)	(0.117)
Total Calls	-0.194***		
	(0.054)		
Total Texts	0.038		
	(0.026)		
In-degree Centrality (C_{in}) – Calls		-0.405***	-0.370***
		(0.075)	(0.102)
In-degree Centrality (C_{in}) – Texts		0.382***	0.362***
		(0.053)	(0.073)
In-degree Centrality (C_{in}) – Calls*Low Status			-0.059
			(0.121)
In-degree Centrality (C_{in}) – Texts*Low Status			0.036
			(0.090)
Phone Number Fixed Effect	Yes	Yes	Yes
Sample Size	7997	7997	7997
-2 Log Likelihood	5079	5039	5039

*$p \leq 0.10$, **$p \leq 0.05$, ***$p \leq 0.01$ (two-tailed tests); standard errors are in parentheses.

Logistic regressions of Study 2 predicting response based on recipients' actual telecommunications patterns for the past three months: independent variables reflect social status, basic usage of mobile services, social connectivity, degree asymmetry, and demographics. All non-dummy variables were z-scores.

We tested the robustness of degree asymmetry by adding three pairs of competing social network variables into the basic logistic regression model: Communications frequency for calls and texts (model 1), in-degree centrality for calls and texts (model 2), and the interaction between in-degree centrality for calls and texts and an experiment condition dummy (model 3). Since the three pairs of network variables were highly inter-correlated (r = .612 to .855), we entered one pair of variables at a time into the logistic regression model to avoid collinearity issues. Again, we converted all non-dummy variables into z-scores. Although in-degree centrality for texts was a significant positive predictor ($p < .001$), and in-degree centrality for calls was a significant negative predictor ($p < .001$), the interaction terms between the two in-degree centrality measures and the status condition dummy were not significant ($p = .625$, $p < .691$ for calls and texts respectively). However, the key variables from the original model, the positive main effect for the status manipulation (p < .001), negative main effect for the weekend dummy (p < .001), and negative interaction between degree asymmetry for texts and the status manipulation, remained significant in all three robustness check models (p = .011 ~ .012).

Appendix 7: Experiment Transcript for Study 3

The experimental context of Study 3 was a 'wrong call' scenario where the requester calls and asks for directions. Research assistants called randomly drawn subscribers from the same city-wise database as previous studies, and used the following transcript during the experiment:

[Research assistants spoke relatively quickly without pause so that the respondent was not given a chance to interrupt]:

> "Hello is this Ouyang Lin[1]? I am Zhu Guoqing[1]. I just got into Chengdu. I'm at the train station now."

[At this stage, respondents were given a chance to say something – usually "wrong number", or "wrong person", before the research assistant caller continues:]

"Oh, terribly sorry, I may have dialled the wrong number. While you are already on the line, could I ask you about something?"

[Code responsivenss score as 0 if respondent hangs up before this point or refuses; respondents get one point for answering each of the following questions]

1) What direction is Wu Hou Ci Park[2] from the train station?
2) Is there a subway line that goes to Wu Hou Ci?
3) Do you know which bus goes there?
4) Is Wu Hou Ci a fun place to visit?
5) How much is there to see at Wu Hou Ci?
6) Is Wu Hou Ci open at night?
7) How far is Wu Hou Ci from Du Fu Thatched Cottage[3]?
8) How long does it take to see Du Fu Thatched Cottage?
9) Are there any other fun places in Chengdu you would recommend?
10) Thanks a lot for your help! Any chance I can give you a call if I have any more questions?

[1] Both Ouyang and Zhu are extremely uncommon family names – customer records indicated no respondent was named Ouyang Lin and it is unlikely for any recipients to have an acquaintance by the name Zhu Guoqing.

[2] A cultural park that is the most popular attraction in Chengdu, and of national repute, which most Chengdu residents should be familiar with.

[3] Another popular attraction that Chengdu residents should be familiar with. Du Fu thatched cottage is a museum and park built around the home of one of the most famous poets in Chinese history.

Appendix 8: Instructions in Manipulation Check for Study 3

For the manipulation check of Study 3, participants received the following instructions and questions relating to their attitudes and perceptions of the caller they just heard his recording:

Context: A visitor comes to Chengdu, has just disembarked at the train station, and ostensibly misdialled while trying to call a friend in Chengdu.

[Participants were then randomly assigned to listen to an audio recording of the experiment transcript read in one of the four accents used in the experiment and then asked to answer the following questions:]

1) How high do you think the caller's social status is? 1[very low] - 9[very high]
2) How high do you think the caller's annual income is? 1[very low] - 9[very high]
3) What do you think the caller's level of education is? 1[very low] - 9[very high]
4) How much power do you think the caller has? 1[very little power] - 9[a lot of power]
5) How much do you like this person? 1[dislike very much] - 9[like very much]
6) If this person accidentally called you and asked for help with directions, how likely would you be to help? 1[very unlikely] - 9[very likely]
7) How far away from Chengdu do you think this person's place of origin is? 1[very close] - 9[very far]
8) How well can you understand what this person is saying? 1[understand absolutely nothing] - 9[understand absolutely everything]

Appendix 9a. Accent Manipulation Check – Means by Condition

	Accent Condition							
	Beijing		Gansu		Putonghua		Zigong	
	Mean	N	Mean	N	Mean	N	Mean	N
Social status	4.59	29	3.62	29	4.58	31	3.52	31
Income level	4.60	30	3.67	30	4.64	33	3.48	31
Education level	5.23	30	3.47	30	5.76	33	3.32	31
Power	3.50	30	2.70	30	4.06	33	2.71	31
Willingness to help	6.70	30	5.73	30	6.64	33	5.42	31
Perceived distance	7.77	30	6.23	30	8.73	33	8.19	31
Cogency	6.40	30	5.93	30	6.67	33	5.74	31
Liking	5.20	30	4.13	30	4.73	33	4.16	31

Predicted responsiveness was actually lower for the low status accents (contrary to the final results of the study), but it is unclear whether this is due to simply mis-prediction or because of social status differences between university students in the manipulation check and the general population in the field experiment.

Appendix 9b. Comparison of Column Means for Manipulation Check[a]

	Group			
	Beijing	Gansu	Putonghua	Zigong
	(A)	(B)	(C)	(D)
Social status	B D		B D	
Income level	B D		B D	
Education level	B D		B D	
Power			B D	
Willingness to help	D		D	
Perceived distance	B		B	B
Understanding accent				
Liking				

Results are based on two-sided tests assuming equal variances with significance level 0.05. For each significant pair, the key of the smaller category appears under the category with larger mean a. Tests are adjusted for all pair-wise comparisons within a row of each innermost sub-table using a Bonferroni correction.

Appendix 10. Manipulation Check Results for Low and High Status Accent Groups

	Low Status Accent	High Status Accent	t-test for Equality of Means		
	Mean	Mean	t	df	Sig. (2-tailed)
Social status	3.57	4.58	4.70	118	< .001
Income level	3.57	4.62	4.88	122	< .001
Education level	3.39	5.51	7.74	122	< .001
Power	2.70	3.79	4.21	122	< .001
Willingness to help	5.57	6.67	3.40	122	.001
Perceived distance	7.23	8.27	3.49	122	.001
Understanding accent	5.84	6.54	1.89	122	.062
Liking	4.15	4.95	2.84	122	.005
Overall social class	3.51	4.85	6.90	118	< .001

A manipulation check confirms that the high status accents were indeed perceived to be higher social status than the low status accents.

Appendix 11: Using the Combined Measure of Number of Questions Answered and Time Spent as Dependent Variable in the Regression Analysis of Study 3

	(A) Without Interactions		(B) With Interactions	
	Beta	*Sig.*	*Beta*	*Sig.*
(Constant)		<.001		.002
Low Status Accent	0.124	.004	.332	<.001
No Knowledge	-0.125	<.001	-.130	<.001
Age	-0.074	.012	-.078	.008
Number of Value Added Services	-0.073	.013	-.072	.014
Smartphone	-0.089	.002		
Smartphone*Low Status Accent			-.130	<.001
Degree Asymmetry (C_{as}) -Texts	-0.085	.003		
Degree Asymmetry (C_{as}) -Texts*Low Status Accent			-.172	<.001

Caller fixed effect	Yes	Yes
Sample Size	1,026	1,026
F-value	20.20	21.21
Adj. ***R*** Square	.144	.151

The results for main effect only (Table 4A) and interaction (Table 4B) regression models were similar even if we use a combined measure of the number of questions answered and time spent responding (seconds) as the dependent variable. The number of questions answered and time spent answering questions were highly correlated (r = 0.84), so we combined the two into a normalized Z-score in the analysis (Cronbach's α = 0.91).

Appendix 12: Note on older 'wrong number' telephone study

It is interesting to note that Goodman and Gareis (1993) previously investigated the impact of social status matching on helping behaviour using a 'wrong number' telephone-based experiment, albeit with no telecommunications or social network data and a different experiment design. However, contrary to the recent literature on pro-social behaviour (Kraus et al. 2012; Piff et al. 2910) as well as our results, they found subjects are more likely to respond to higher status requesters. It is possible that this was because Goodman and Gareis (1993) only operationalized status of the requester with two specific occupations (lawyer or gas station attendant), which might have yielded occupation-specific biases (e.g., some high status individuals might dislike lawyers, while some low status individuals might dislike gas station attendants). In addition, they found a null result in status matching (homophily) effects. However, this was likely because the study used the median income of only two neighbourhoods as a proxy for respondents' social economic status, which might have been too small or biased a sample to observe the effect. However, that similar research questions and designs have not been revisited for a quarter-century, even after major advances in researchers' data capabilities highlights an opportunity for future research, particularly given the recent increased interest in social status effects (Jordan et al. 2014; Kraus et al. 2012; Piff et al. 2010).

REFERENCES

Goodman, Michael D., and Karen C. Gareis (1993). The Influence of Status on Decisions to Help, *The Journal of Social Psychology*, **133** (1), 23-31.