Is Deservingness Merit-based or Need-based? Evidence from Medical Crowdfunding

CHEN Junhao

Boston University

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Abstract. This paper studies how donors respond to merit and need when giving to families facing unaffordable medical expenses. With data from a leading crowdfunding platform in China, I find that campaigns receive more donations if recipients report having a higher education level or attending more selective colleges. The college rank effect persists even after controlling for content and textual characteristics and donor fixed effects. To identify the effect of donor preference, I conduct an online survey experiment to elicit the willingness of respondents to donate to fundraising vignettes, in which the patients' college and medical expenses are independently randomized. Both academic merit and financial need enhance donor generosity. Female and younger respondents respond more to need and less to merit. The college rank effect is more pronounced for top and in-province institutions and among people with better knowledge of the ranking. Merit helps attract donations, likely by enhancing perceived deservingness. Novel textual methods based on large language models are developed to extract information and build measures from fundraising stories efficiently.

Keywords: donation, merit, education

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Introduction

Health shocks and medical expenses push millions into poverty globally (WHO, 2017).[1] Besides loans and relief packages, crowdfunding has become a new lifeline for patients facing unaffordable medical expenses. In recent years, crowdfunding platforms have helped raise billions of dollars around the world, providing crucial support for millions of families in urgent need. However, fundraising outcomes can be highly unequal on these platforms, with a few viral campaigns taking the lion's share while others receive little. Unsurprisingly, crowdfunding platforms are constantly questioned about their fairness in this matter of life and death.

In this paper, I examine how academic merit (college selectivity) and financial need (medical expenses) of the recipients affect donor generosity in both real-world scenarios and experimental settings. The abundance of data on crowdfunding platforms has helped further understanding of charitable fundraising (Meer, 2014, 2017). However, few papers have investigated the narratives in fundraising campaigns despite their being informative about donors' motivation and social preferences, i.e., who deserves the help and under what circumstances. By examining donors' attitudes toward the educational credentials of recipients, I shed light on the general perception of individual worthiness and the profound influence of meritocracy in society.

With 144,000 campaign profiles scraped from *Qschou.com*, a leading medical crowdfunding platform in China, I document that recipients attending college or more selective ones received a higher total donation at the campaign level. For a subsample of campaigns reporting the name of colleges attended by the patient or the fundraiser,[2] I obtain the full donation records and construct a unique dataset at the transaction level, where donors are identified and tracked across campaigns. After controlling for diseases, expenses mentioned, patient demographics, donation sequence, and many other covariates, I show that, within a repeat donor observed in multiple campaigns, more donations are given to the patient who attends a higher-ranked college or a postgraduate program. In doing so, I construct variables of interest and covariates with the help of various textual methods.

This within-donor specification largely eliminates the effect of social network disparity, i.e., rich people get help from their rich friends. I also verify that the variation in tie strength between donors and recipients is not driving the results. Furthermore, the academic merit effect is not fully explained by the fundraising ability measured by text length, writing quality, and narrative features. The rank gradient in donor generosity is steeper among the top 100 colleges and when patients attend in-province colleges, suggesting donors have limited information on college ranking. From each donor, a young adult patient attending a top 30 college received CNY 2.4 more (24% of the median donation) than someone attending a college ranked beyond the 800th, while students from colleges ranked between the 400th and 800th hardly benefit from college reputation. In line with inequity aversion, donors moderately react to the medical expenses mentioned in the story.

[1] According to WHO, 800 million people spent at least 10% of household budgets on health expenses in 2017.
[2] Fundraiser is defined as the narrator of the fundraising story

Though carefully crafted and validated, my measures of writing qualities may not fully capture storytelling skills and emotional appeal, which may contribute to the academic merit effect in the observational results. To provide causal evidence on the donor preference channel and explore donor heterogeneity, I designed an online survey experiment emulating an actual donation scenario. Following Neumark et al. (2019) and Kessler et al. (2019), I present to the respondents 16 synthetic vignettes about a college-educated young adult patient who needs help with medical bills. At the vignette-respondent level, I independently randomize two vignette components: college tiers of the patients and the amount of medical expenses. Respondents are incentivized by real-world consequences to truthfully report donation intentions to each vignette.

In line with the observational results, the willingness to donate in the experiment is higher for vignettes that depict patients attending the top 50 colleges and mention higher expenses. The effect of the college tier is much more pronounced among half of the respondents who know more about the college ranking and when respondents encounter local colleges, confirming the importance of information in revealing the preference for college selectivity. The response to financial need relative to academic merit is substantially larger in the experiment than in the observational results, presumably due to less available information on the medical condition and financial situation presented in a short vignette than in an actual fundraising story.

Graduation status also matters for donor generosity. In both the field and experiment settings, people respond more to college rank if the patient is a current student rather than a recent graduate. This suggests donors infer a higher income and less deservingness from the credentials of the graduates, and thus discount their past achievements in deciding on the extent of support. This result is consistent with a model for impact-seeking donation behaviors. The model also predicts that more egalitarian people respond more to the need and less to the merit, which is indeed observed in the experiment. In addition, males, the middle-aged, those with a higher self-reported income, and those attending higher-ranked colleges behave in a more merit-oriented and less need-oriented way in the experiment.

Donors also favor young patients over their senior family members. From each repeat donor, a young patient received CNY 0.6-2.2 (6-22% of the median donation) more than a senior patient with a comparable family background. The disparity at the campaign level is more stark as the extensive margin is incorporated, with young patients receiving nearly twice as much. This shows that donors take into account the life-years gained from sponsoring a patient (Murphy and Topel, 2006; Aldy and Viscusi, 2007). Both the academic merit effect and patient age effect provide evidence that donors generally seek impact by donating more to worthy patients whose cures would make a bigger difference to their family, community, and society. Instead of a passive buffer against financial shocks, donation to individuals is an active shaping force of society as it allocates resources preferentially among the most vulnerable groups like patients.

Conventional textual methods and novel approaches built on large language models (LLMs) are employed to extract information from text quickly, accurately, and cost-efficiently. For example, I identify the diseases by Named Entity Recognition and the relationship between the fundraiser and the patient by Coreference Resolution. I evaluated the writing quality of stories by exploiting the versatility of *ChatGPT*, instructing it to count grammar errors and rate fundraising stories based on rubrics adapted from TOEFL writing. The performance of routines built on the *ChatGPT* largely exceeds that of more conventional textual methods or previous language models. For example, the accuracy of extracting context-relevant information easily reaches 90% or higher with *ChatGPT*, compared with around 60% with language models with fewer parameters and trained specifically for question answering in Chinese.

This paper makes several contributions. On the methodological side, I developed routines based on the newly available language models that excel at information extraction. These routines can be easily adapted to accomplish other tasks, demonstrating the great prospects of applying generative AI in empirical research in social science. On the empirical side, it is the first paper to provide field evidence of the impact of academic merit on distributional preferences. It is also one of the few studies on distributional preferences in China, a more meritocratic society than the U.S. or Nordic countries that previous studies focused on. On the theoretical side, I explore the interplay between the perceived need and merit of the recipient in determining donor generosity and show how these two motives compete with each other.

College selectivity improves labor market prospects. Gaddis (2015) showed in a resume audit study in the U.S. that a credential from an elite university results in more employer responses. Similar results are found in Canada (Mullen et al., 2021) and the U.K. (Drydakis, 2016). Using regression discontinuity design, researchers found attending elite colleges leads to higher income in the U.S., Europe, and China (Hoekstra, 2009; Anelli, 2020; Jia and Li, 2021). College prestige plays an important role here. Sekhri (2020) finds graduates of elite public institutions in India have higher earnings even though attending these colleges has no discernible effect on academic outcomes. MacLeod et al. (2017) finds that additional information on the skill of the graduates from a newly introduced college exit exam reduced the return to college reputation in the labor market.

It is also well known that education leads to non-wage benefits like improvement in health outcomes and marriage market opportunities. This paper finds that students from selective colleges get more help when asking for money in dire situations, indicating that the return on (selective) college attendance is more extensive than previously documented. Part of the effect comes from abilities. Academic high-achievers write longer and better stories, which helps attract more donations. On the other hand, donors react to educational signals, treating students from elite colleges favorably.

My paper also relates to the role of merit and worthiness in shaping distributional preference. Researchers have found that people (prefer to) redistribute less when told that the inequality is due to merit or effort instead of luck (Alesina and Angeletos, 2005; Durante et al., 2014). Even a little bit of merit makes people significantly more inequality accepting (Cappelen et al., 2023). The setting of medical crowdfunding differs from these works in the magnitude of shocks the patient suffered and in the urgency of receiving timely treatment. In fact, my model allows for the case that academic credentials harm the fundraising prospects if the financial shock is small enough or when the general perception of college selectivity is associated more with advantageous family background and less with merit.

In a close paper, Gangadharan et al. (2023) found in a field experiment that information regarding recipients' attending courses and being non-alcoholic increases donors' giving. Fong (2007) and Fong and Luttmer (2011) found altruism is conditional on recipient worthiness: when donating to low-income recipients in a dictator game, donors gave more generously to those who appear more industrious or had fallen into poverty due to bad luck. My paper differs from the literature by focusing on merit embodied in well-recognized credentials rather than recipients' efforts to escape poverty or their performance in relatively trivial laboratory tasks.

1 Background

1.1 Medical Crowdfunding

1.1.1 Demand for Medical Crowdfunding

There are significant economic costs associated with major illness. First, despite the wide coverage of health insurance[3], out-of-pocket costs could still be unaffordable if involving reoccurring treatments (e.g. chemotherapy, hemodialysis), surgery (e.g. organ transplant), or exceeding coverage limits (e.g. prolonged ICU stay). The medical conditions in a crowdfunding campaign largely fall into these three categories.

Second, illness limits the earning potential of patients and burdens the family with caregiving responsibilities. According to an official survey in 2016, 20 million people in 7.75 million households have been pushed into poverty by illness, accounting for 44.1% of all causes of poverty. From 2018 to 2020, the Chinese government approved a total of 330 billion CNY in medical bills forgiveness.[4] Expenditure of such scale helps fight poverty but also causes a considerable fiscal burden.

Third, even if a medical bill is affordable, a household still has strong incentives to buffer the financial shock by liquidating social capital. As evidence, Gertler and Gruber (2002) found household consumption drops over illness episodes.

1.1.2 The Rise of Medical Crowdfunding

Medical crowdfunding helps match the abundant supply and demand in charitable giving related to major health shocks. In a crowdfunding campaign, the fundraiser posts the medical information and fundraising story on the campaign page, spreads the message via group chats and social media, and receives small donations from many donors to cover the medical bills or finance surgery.

[3]As of 2020, about 95% of China's population has at least basic health insurance coverage.
[4]Source: https://www.gov.cn/xinwen/2020-11/21/content_5563157.htm

With the rise of messaging apps, social media, and mobile payments, crowdfunding platforms have been expanding rapidly in China since 2015. The two leading platforms have helped raise about $9 billion for medical-related causes. Statistics from these firms show that around 400 million people have donated to 3 million crowdfunding campaigns, meaning that 1 in 3 Chinese have participated. In 2020, medical crowdfunding accounts for around 5% of China's total charity donations.

There are several reasons for the success of medical crowdfunding platforms. First, helping a specific individual or family brings a greater perceived impact compared to donating to a charitable fund. Second, severe illness and injury are usually associated with bad luck, so these patients deserve sympathy. Third, the power of asking can be strong, especially when your friends and relatives share the fundraising appeal. Culture contributes to the popularity of medical crowdfunding in China. It is a Chinese tradition to give gift money when visiting a patient, as well as when attending a funeral or a wedding.[5] Therefore, the Chinese are accustomed to donating to patients in need.

1.2 Platform Mechanism and User Behaviors

Throughout the paper, a *fundraiser* refers to the narrator of the fundraising story and is expected to be the person who manages the campaign. A *patient* refers to someone who, due to disease or injury, requires donations for medical treatment. A *recipient* can refer to the patient, the fundraiser, or sometimes their family, since fundraising is often a joint effort of all family members. On *Qschou*, middle-aged or elderly patients are fundraised by children or other young and tech-savvy relatives. Young adult patients are fundraised by classmates, siblings, cousins, significant others, or themselves if the condition is not acute.

After creating the campaign page, the fundraiser spreads the message (with a link to the campaign) among friends and relatives via group chat and social media. Viewers of the campaign page help by donating and spreading the message on social media. The platform also showcases campaigns on its website and app, but that only accounts for a fraction of the donation source.[6]

Narratives

Fundraisers are required to post a story describing the reasons for initiating fundraising. The story is typically 100-500 words, introducing the family background, fundraising efforts, and medical condition. A successful campaign often presents a compelling story that resonates with the readers, urging them to share it with a wider audience.

Fundraisers emphasize the merit and need in the stories. They depict the patient as a strong and resilient person who supports the family and contributes to society. Most fundraisers also highlight low income, heavy debts, high medical expenses, and the ensuing strain on

[5] Such "relational expenditure" accounts for 4-10% of the total expenditure of an average family in 2016. Source: China Family Panel Studies 2016

[6] An interview with an industry insider confirms that WeChat (similar to WhatsApp combined with Facebook) accounts for more than 80% of the donations inflow.

the entire family. Medical conditions are described as painful, handicapping, and often life-threatening. A fraction of patients reportedly died during fundraising[7]. It is worth noting that the narrators always depict the disease as a sudden strike of bad luck or a result of the toil of work, and prevent the donor from associating the medical condition with the patient's lifestyle. Attributing unequal social and financial outcomes to luck will likely persuade donors to "redistribute" more (Alesina and Angeletos, 2005).

To ensure the authenticity of the story content, the platform implements measures that include photo requirements, medical document verification, and endorsement by friends and relatives. The platform also relies on user reporting to fight fraud or abuse. My analysis focuses on academic merit and financial need, as they are two frequently reported narrative components that are quantifiable.

Target Setting

The fundraiser sets a target amount during the campaign, and the target can be modified anytime as needed. The target is largely non-binding since the fundraiser can always claim the full amount donated to the campaign in the end, regardless of the target being achieved or not. When the inflow of donations is anticipated to surpass the target, I observe that fundraisers often raise the target rather than let the campaign end by achieving the target. They also terminate the campaign in advance when there is a significant halt in incoming donations. Therefore, it is unlikely that the perceived impact of a donation is strongly associated with the fundraising target or progress.

1.3 Colleges in China and its Perception

In China, the public perception of selective colleges is overwhelmingly positive. Students attending these colleges are often seen as diligent and intelligent rather than having privileged backgrounds. Associating college selectivity with merit is well justified. First, college admission is almost entirely determined by the performance on the college entrance exam, *GaoKao*.[8] The transparency and straightforwardness in the admission process ensure procedural fairness and avoid controversy like legacy admission in the U.S.

Second, the high regard for prestigious colleges is deeply embedded in Eastern Asian culture. During its 1,300-year history, the civil examination system, *Keju*, served as almost the sole pathway for ordinary Chinese to ascend to the elite class. And it even shaped contemporary human capital outcomes through channels including cultural transmission (Chen et al., 2020). As a continuation of this prominent social ladder, people celebrate and honor those who made it into prestigious colleges by excelling at the entrance exam. It is not uncommon for students admitted to top colleges to receive prizes and cash awards from their high school or local entrepreneurs. As a downside of glorifying selective colleges,

[7] Approximately 1% in my sample

[8] College admission is mainly determined by the entrance exam, except for admission for student-athletes and art students. Also, limited autonomy is granted to dozens of top colleges

young people without college degrees or going to less selective ones often feel discriminated against when seeking a job or attempting a career advancement.

It is harder to infer family background from one's college in China than in countries like the U.S., where large income segregation across colleges is documented (Chetty et al., 2020). First, college tuition is affordable. Public institutions accounted for 80% of college enrollment in 2018. Annual tuition typically ranged from CNY 5,000-8,000 (USD 700-1,100) for common majors, or less than 10% of the national average annual wage in 2018, compared to a stunning 18%-55% in the U.S. Second, tuition waiver and state-funded need-based financial aid are easily accessible.[9] Both contribute to low dropout rates (1-3%) in Chinese colleges. Therefore, family income would be less of a constraint in college choice.

In addition, intergenerational mobility in education is not compromised by parental educational disparities. The expansion in tertiary education in China started in 1999, and recent college students are mostly first-generation students. For these reasons, income segregation is expected to be mild in China's colleges, fostering a more favorable public perception of college selectivity.

2 Data

2.1 College Rankings

In 2019, there were 2,688 post-secondary degree-granting institutions in China, and 1,265 of them were permitted to grant bachelor's degrees. College quality is measured by the national college ranking published by *Shanghai Ranking*, a consultancy similar to the *QS Ranking*.[10] It dominates other rankings on Chinese colleges in its comprehensiveness and methodological rigor. College characteristics such as type and location are obtained from *Yiqixue.com*.

I chose the ranking in 2022 for its wider coverage (811 institutions in total) than previous ones and college ranks are largely invariant with time. The ranking considers all institutions that grant bachelor's degrees in mainland China with at least 100 full-time faculty members. In my analysis, colleges outside of this ranking are grouped into the category of unranked colleges. College campuses outside of the prefectures of the main campus and independent colleges are treated as separate institutions which almost always fall into the category of unranked colleges. Campaigns regarding colleges outside of mainland China are omitted.

2.2 Fundrasing Campaigns and Donations

I scraped 144,000 campaign pages from *Qschou.com*[11], the second largest medical crowdfunding platform in China. Links to these pages are collected from Weibo, a Twitter-like

[9]Few admitted students would give up attending college for financial concerns, except for attending the least selective for-profit colleges that charge higher tuition

[10]https://www.shanghairanking.com/methodology/arwu/2022

[11]Non-medical-related campaigns account for less than 8% of total campaigns on *Qschou.com*. The Chinese name *QingSongChou* means "easy fundraising"

social media, where the fundraisers post requests for help.[12] My sample constitutes the near universe of *Qschou* campaigns posted on Weibo during 2015-2018, or at least 6% of the total campaigns during the same period. The campaigns in my sample are expected to be more successful than average. This is because posting on a public-oriented social media like Weibo, instead of relying only on the friend-oriented messaging app of WeChat,[13] indicating a fundraiser is more tech-savvy than average and more confident in the appeal of her case to socially distant donors. My campaign sample has wide coverage in terms of geography, medical conditions, and patient demographics.

I scraped all campaign-level information from the webpages other than photos. This provides us with almost the same information that a socially distant donor may have. Basic information like fundraising targets and donation records are directly obtained from scraping the page. Based on the content of the fundraising story, I constructed the variables of interest and various covariates. See Table A2 for a list of variables. For the campaigns in the main sample groups that I define below, I further obtained their entire donation records, from which we observe how much was donated by whom at what time, together with the comments from the donor or the fundraiser.

2.3 Sample

2.3.1 Sample Selection at the Campaign Level

To construct the main sample, I first searched the fundraising stories for the official names of colleges. I then verified if the mentioned college is or has been attended by either the patient or the fundraiser rather than being a workplace, an affiliated hospital, or related to another family member mentioned in the story. Over 5,600 campaigns, or 4% of the population, are matched to a college in this step, while mentions of colloquial names of colleges are omitted. Next, campaigns with the following characteristics were excluded from the study: 1) fundraising for multiple patients, 2) institutions affiliated with the college, and 3) the patient died.

There are several reasons to mention college names in the fundraising stories. First, when a current student is fundraising or has fallen ill, it is natural to mention her college as part of the introduction. Second, it helps solicit donations from alumni, as fundraisers also target other ingroup members by mentioning middle school, hometown, and workplace. Another reason is to signal merit, particularly to potential donors unfamiliar with the recipient family. Also, fundraisers sometimes emphasize that as college students they don't have any income and have to seek help from crowdfunding.

[12]Links to the fundraising campaigns are collected in 2019 and credited to GUO Xinyan
[13]China's counterpart of WhatsApp combined with social media features similar to Facebook

2.3.2 Main Sample Groups

I group college-related campaigns into two broad categories based on the age of and relationship between the fundraiser and the patient. The main analysis relies on the following two groups, especially the group of young adult patients.

Group A: Young Adult Patient In this group, the patient is a college student or graduate aged below 40 and with no children. The narrator is either the patient themselves, another young adult, or a third person whose identity is not specified (45.8%, 41.7%, and 12.5%, respectively). The college name of the patient is reported, and campaigns reporting college of the fundraiser are excluded from this group.

Group B: Fundraising-for-Senior Campaigns in this group are narrated by a college student or graduate aged below 40 and having no child. The patient is their senior family member, usually a parent. The college name of the fundraiser is reported, and the educational background of the patient is rarely mentioned since very few of them attended college. The median patient age is 49 and most of the fundraisers are in their 20s.

Table 1: Sample Composition at the Campaign Level

Sample Size	College attended by	Fundraising for oneself	Fundraised by a young adult	Total
Young adult patient	Patient	659	600	1,443 [a]
Senior patient	Fundraiser		2,003	2,003

[a] including 184 campaigns where the narrator is a third person whose identity is not specified

The two groups constitute the majority of the matched cases. Of the remaining 4,058 college-related campaigns, 1,443 fall into the young adult patient group and 2,003 into the fundraising-for-senior group. The other 612 cases are discarded, many of which regard a college graduate fundraising for a newborn, a parent fundraising for their child in college, or mentioning two or more individuals attending college. In the young patient group, I pooled campaigns that vary in the fundraiser-patient relationship to guarantee the sample size.

By focusing on these two groups, I ensure that comparisons are made among homogeneous recipients, alleviating potential bias from unobserved attributes. First, patients and fundraisers are highly homogenous within each sample group. Second, the families are also similar across sample groups. In both groups, the younger generation is in their 20s or 30s and attends college, indicating their families have a comparable socio-economic status and are in the same stage of family life cycle. On the other hand, the contrast in the patient's generation helps test whether donors respond differently to the merit of the patients and that of the fundraiser.

3 Methodology

3.1 Natural Language Processing

Textual methods laid the foundation of my empirical analysis, as most variables of interest and covariates are built from the content of the stories. Also, I construct various writing characteristics that serve as controls for fundraising ability. To achieve these goals, I implement two types of natural language processing (NLP) tasks: conventional ones based on parsed text of stories and novel methods leveraging the versatility of large language models (LLM). Manual proofreading and revision are conducted whenever necessary.

It turns out that LLMs like ChatGPT not only can accomplish tasks that previous language models struggle with, but also perform better in tasks achievable by more traditional textual methods. For example, information extraction using ChatGPT is much more accurate than using smaller language models and more straightforward than building on linguistic-based methods. Of course, the inference cost increases with the number of parameters in a language model, and researchers need to pay for using models like ChatGPT. But that cost is only 1-10% of hiring research assistants to perform the same task. At the same time, the price of ChatGPT API has been rapidly going down and open-source LLMs are emerging. As a result, the use of generative AI in empirical research is extremely promising.

3.1.1 Conventional Textual Methods

RegEx Context-irrelevant information and strings of straightforward patterns can be efficiently extracted by regular expressions. For example, in constructing the college sample, I searched for full college names in the text, excluding cases related to an affiliated hospital or a workplace.

Named Entity Recognition During text parsing, Named Entity Recognition (NER) identifies categories of words used in defining covariates, such as diseases, locations, and organizations. For instance, to determine the patient's home province, I employ NER to detect mentions of full or partial addresses or county, town, or city of residence.[14] I then geocoded the names of places to generate the variable of *home province*.

Miscellaneous The relationship between patient and fundraiser is defined based on Coreference Resolution (He and Choi, 2021), a task to determine which pronouns in a text refer to the same entity. Text summarization and keyword extraction are applied in some steps to enhance performance. I also used a leading essay editing tool, *Xiezuomao*, to measure linguistic characteristics like word positivity and emotional intensity.

3.1.2 Method based on GPT

I developed an easy-to-use and cost-efficient routine to extract information from text using large language models (LLM). I pose questions to ChatGPT about the story content and

[14] Confounding instances like workplace are excluded.

then extract key strings from its response to construct variables. This routine requires only basic textual expertise to set up, but its performance usually exceeds that of NLP practices based on parsed text, due to GPT's strength in understanding the context.

Prior to ChatGPT, many language models have been trained for question-answering tasks. By comparison, ChatGPT can achieve high accuracy and adaptability, while previous Q&A system models often struggled with tasks not closely aligned with their training data.[15] To guard against "hallucinations" and any factual mistakes in ChatGPT's response, I validate the output throughout the process. Take information extraction tasks for example, incorrect responses and falsely reported missing values are rare (usually less than 5% combined) when providing the model with properly engineered prompts and comprehensive instructions. As a result, routines leveraging LLMs easily replace human research assistants in labor-intensive text-related tasks.

The typical workflow is a trial-and-error process in a sense similar to fine-tuning. First, when designing the prompt, you manage to pose clear questions, provide detailed instructions, and specify the desired output format. Then, you validate the prompt on a subset of your dataset, evaluate the response in terms of accuracy and ease of parsing, and refine the prompt iteratively. Finally, you extract strings from the responses and generate variables accordingly. For practitioners, see Appendix A.1 for a detailed walkthrough. The methods and relevant variables are described below.

Variables on Content Using the OpenAI ChatGPT API, I generated variables from the fundraising stories, including disease category, patients' age and sex, graduation status of the college student, and medical expenses mentioned. A sample prompt would be as follows, *"Extract the information based on the content of the following article. Print one answer on each line. Do not repeat the questions. If not sure, you can answer 'not mentioned'. Q1: What illness does the patient have? Q2: How much is needed in total for medical treatment?...[List of questions continues]...[Input story here]"*

Writing Quality I instruct ChatGPT to rate writing quality using marking rubrics adapted from TOEFL writing. The task is essentially a zero-shot classification based on descriptive instructions. The rating includes four dimensions: persuasiveness of content, organization and coherence, wording precision, and literary grace. Each dimension received a subscore between 1 and 5, and the sum of subscores provided an aggregate rating. The outcomes are validated by human evaluation. Figure A1 shows that the human rating on writing quality strongly correlates with language model output, although ChatGPT seems to struggle with distinguishing the best writing from the good ones.

Grammar Errors I instruct ChatGPT to identify all non-trivial grammar errors or word choice problems while allowing for colloquial expressions. Benchmarked against human evaluations, the GPT-4 responses yield less than 10% false positive (flagging a non-mistake) and less than 20% false negative (leaving out an actual mistake). [16]

[15] LLM is neither language-specific nor task-specific, and have excellent generalization ability

[16] In detecting grammar errors, GPT-4 significantly improved on GPT-3.5 and by far dominates any other models or automated editing services in Chinese as of September 2023.

Topic Coverage I instruct ChatGPT to count the sentences on topics like diagnosis, treatment, family background, medical expenses, etc.[17] I then calculate the relative coverage on each topic by dividing the topic-specific sentence counts by the total sentence count across the listed topics.

Table 2: Comparison of Methods in Information Extraction

	Accuracy	
	Context irrelevant	Context relevant
String match (RegEx)	High if taking care of all contingencies	Not applicable
Previous pre-trained language models [a]	60-90%	50-90%
ChatGPT API	>90%	>90%
	Cost [b]	
	Monetary	Time
String match (RegEx)	Zero	Not a concern
Previous pre-trained language models	Require local or cloud computing power	500-5000 documents per PC per day
ChatGPT API	$10-200 per 1000 documents	1000-5000 documents per thread per day
	Ease of Use	
String match (RegEx)	Easy to employ	
Previous pre-trained language models	Difficult. Fine-tuning typically needed to achieve good performance.	
ChatGPT API	Moderate. Fine-tuning not necessary.	

[a] Language models before ChatGPT, typically with much fewer parameters
[b] Costs depend on the task, number of parameters in a language model, and computing power available. A document means roughly 500 English words

4 Conceptual Framework

This section introduces a simple framework illustrating how recipients' (perceived) merit and the size of negative shock affect the donation decision. Donors derive altruistic utility from lifting a family in real distress. The joy of giving increases with the recipient's merit, as donors prefer helping more worthy people. On the other hand, recipients vary in family wealth, and donors would like to avoid donating to recipients who can pay for their medical treatment without external help. Therefore, the perceived need of the recipient increases with the reported shock size but decreases with the (academic) merit, as merit indicates a wealthier family background or a higher household income.

To focus on the mechanism of interest, I assume donors derive altruistic utility only from the act of giving, without consideration for the recipient's overall outcome, which is also determined by donations from other donors. In other words, I only incorporated the warm glow effect, but not the pure altruism effect. This assumption fits the context of medical crowdfunding, as donors continue to give small donations after observing that tens of thousands of funds have been raised (and effectively obtained) by the fundraisers.

$$U_i = \underbrace{f(w_i - \Sigma_j g_{ij})}_{\text{Consumption}} + \alpha_i \cdot \underbrace{\Sigma_j \pi(s_{ij}, m_{ij})}_{\text{Perceived Impact}} \cdot \underbrace{V(m_{ij}, g_{ij})}_{\text{Altruistic value}} \tag{1}$$

[17] The topics are as follows: 1)illness, diagnosis, treatment, and surgery, 2)patient biography and family background, 3)medical expenses, fundraising effort, and financial standing, 4)appeals, expressions of emotions, and gratitude, 5)merit of patient, 6)bank account and transfer details, 7)any content not mentioned above.

In Equation 1, g_{ij} denotes the donation from donor i to recipient j. m_{ij} and s_{ij} denote the perceived merit and the size of the shock. The donor derives utility from consumption, $w_i - \Sigma_j g_{ij}$, and the joy of giving. The latter depends on the altruistic parameter a_i, the perceived need of the recipient π, and the perceived worthiness of the recipient captured in $V(m, \cdot)$. The interpretation of π is the subjective probability that the patient's family is not self-sufficient when facing shocks, which increases with shock size s and decreases with m.

$$U = w - g + \alpha \cdot \frac{s}{s+m} \cdot (V_0 + vm) \cdot \ln(g+1) \tag{2}$$
$$\text{with } m \in (0,1],\ s \in [0,1],\ v > 0, \text{ and } \alpha > 0$$

The insight can be concisely illustrated in the example in Equation 2. There is only one potential recipient, v captures the public perception of the importance of merit in determining recipient worthiness *relative to* its perceived importance in determining household wealth. A larger v corresponds to a society that is more meritocratic and/or has lower income segregation across levels of merit (i.e., colleges in our case). The term $s/(s+m) \in [0,1]$ captures the capability of the recipient family to buffer the shock on their own, or it could be read as the perceived impact of each dollar donated, which decreases with recipients' endowment at the time of fundraising (Duncan, 2004). $V_0 > 0$ is a parameter denoting the value of saving life regardless of the merit. A larger V_0 relative to v means that an individual donor is more egalitarian. The other parameters have the same meaning as in Equation 1.

The optimal donation is,

$$g^* = \max\{\alpha \cdot \frac{s}{s+m}(V_0 + vm) - 1, 0\} \tag{3}$$

Assuming no corner solutions, optimal donation increases unambiguously with perceived financial shock, as

$$\frac{\partial g^*}{\partial s} = \alpha \frac{m}{(s+m)^2}(V_0 + vm) > 0 \tag{4}$$

And the merit gradient in donation is,

$$\frac{\partial g^*}{\partial m} = \alpha s \frac{vs - V_0}{(s+m)^2} \tag{5}$$

Therefore, we expect donations to increase with merit when $vs > V_0$. In other words, as long as the shock is large enough or the public perception of college selectivity is not too correlated with family background relative to recipient worthiness, we should see more donations given to meritorious recipients. Figure A2 provides a more specific numerical example. In the real world, a smaller v corresponds to the case of the U.S., where college selectivity strongly correlates with socioeconomic status. Whereas in China, v is larger as people hold (selective) colleges in high regard. In the case of medical crowdfunding, s is large because the reported medical condition is usually critical. Suppose that a couple of fundraisers with varying family background are seeking donations for dental fillings. Seeing their appeals, potential donors might be more willing to support fundraisers with few educational credentials, as donors infer that these people are more likely to have a low income and thus need help even with a relatively small expense.

V_0 captures equity-mindedness of the donor, donors with a larger V_0 care about helping recipients without regard to their merit. Two additional results to be invoked in later sections are as follows,

$$\frac{\partial^2 g^*}{\partial m \partial V_0} = \frac{-\alpha s}{(s+m)^2} < 0 \quad , \qquad \frac{\partial^2 g^*}{\partial s \partial V_0} = \frac{\alpha m}{(s+m)^2} > 0 \tag{6}$$

Equation 6 shows that more meritocratic (less egalitarian) donors, i.e., those with a smaller V_0, would have a larger response to merit and a smaller response to shock.

5 Analysis

5.1 Summary Statistics

Crowdfunding campaigns are typically funded by numerous small donations. As shown in Figure 4, the outcome distribution at the campaign level is highly skewed. The average donation in my main sample is CNY 25.7 (USD 3.6), and the median is CNY 10 (USD 1.4).[18] An average campaign reporting recipient's college receives donations from 2,385 donors, suggesting they receive donations from not just first and second-degree connections but probably more socially distant donors. Around 70% of the campaigns in our main sample mentioned the amount of medical expenses, which is defined as either an anticipated expenditure or a medical debt. Variables like college rank, postgraduate proportion, college in-province status, and writing quality are balanced in two main samples, although college students fundraising for a senior family member are more likely to be a current student as opposed to a graduate (82% vs. 56%) and mention a 44% smaller medical expenses. See Table 4 for details.

As suggestive evidence of "college premium", Table 3 shows that the campaigns with the recipient's college matched are much more successful than the others, a result that appears to be driven by the extensive margin.

In our main samples of campaigns with recipients' college reported, college selectivity and expense amount mentioned are both strongly associated with aggregate fundraising outcomes (See Figure 6 and Figure 7). The college rank gradient is steeper among more selective colleges while the expense gradient is largely linear. Several potential mechanisms may play a part in driving this pattern.

[18] The mean is CNY 38.7, or USD 5.4, before truncation of the largest 2.2% donations

5.2 Potential Mechanisms

Social Capital

Social capital helps households cope with economic shocks, but the family varies in the size of their social capital. This is because social ties exhibit substantial homophily by social-economic status (SES). People with high SES are more likely to befriend those who have higher SES (Chetty et al., 2022a). In our case, families with younger generations attending selective colleges may have more high-income friends to seek help from. Moreover, if a person of high SES shares a fundraising appeal on her social media, it circulates among a high-SES network.

In addition, college attendance creates social ties. Chetty et al. (2022b) point out that the differences in exposure to people with high SES in groups such as schools explained half of the social disconnection across socioeconomic lines. Jia and Li (2021) find that those just above the admission cutoff of elite colleges have peers with more advantageous parental background. Also, it is not uncommon for an alumni association or student union to participate in fundraising and spread the fundraising appeal among a larger social network.

Therefore, people attending (selective) college generally have more social capital to resort to in times of need. This disparity is expected to be a major driver of the differential fundraising outcome. Indeed, I find the average donor level of a campaign, an indicator of cumulative donations on the platform, is positively associated with recipients' college selectivity. The importance of social capital in online crowdfunding is also illustrated in Figure A3, where I found the platform has a higher penetration in prefectures where clan culture is stronger, proxied by the density of family shrines.[19]

Ability and Effort in Fundraising

Admission selectivity and college education are associated with higher ability, which translates to better campaign quality. Those from higher-ranked colleges write better stories, as shown in Figure 8. In addition, they may be more diligent and post updates more frequently on social media. Similarly, those who report a higher medical expense might also exert more effort in fundraising to buffer a larger financial shock and solicit donations from more potential donors, which leads to a larger donation amount received at the campaign level.

Selection into Platform

Soliciting donations from people in your social network makes you lose face. Therefore, people may initiate crowdfunding as a last resort. If families with a younger generation attending a selective college are wealthier, they may turn to crowdfunding less often, relying instead on saving or borrowing to buffer a shock. And when they resort to crowdfunding, they might be hit by a more severe health and financial shock, making the case more compelling to potential donors.[20] On the other hand, people attending more selective

[19] There are more fundraising campaigns in Guangdong, Guangxi, and Fujian, family shrine data from China Family Panel Studies

[20] Similarly, people might hesitate to monetize their college's prestige for personal purposes, and those who do so can be in deeper distress.

colleges can be more tech-savvy, lowering the time cost for them to set up a fundraising page, leading to less severe medical conditions in their crowdfunding campaigns. There is mixed evidence on the direction of selection. As shown in the bottom right panel in Figure 8, the correlation between college rank and expenses mentioned suggests the former case. However, Figure 5 shows that more selective colleges are over-represented in our main sample and suggests the opposite.

Donor Preference and Belief

Donors may think like social investors, seeking to maximize the impact when donating. There are at least two things donors could infer from recipients' college selectivity: 1) Some patients are more talented and, once they are cured, will have a promising future and contribute a lot to society, 2) Some recipients are more capable of managing money and are less likely to misappropriate or squander donations by seeking quack remedies. In addition, in China, college selectivity is seldom associated with family background for the lower tuition and more equitable and transparent admission process compared to countries like the U.S. Taken together, I expect potential donors are more willing to donate to those who attend(ed) selective colleges, other things equal. The experiment analogy of preference channel would be to randomize college names that potential donors see in the stories.

Also, mentioning a higher expense amount would likely help persuade people that the medical condition is severe and the financial shock substantial. Although the fundraisers do have an incentive to overstate the expense, the expense amount is partially verifiable because donors typically upload photos of diagnoses and bills. Donors who care about equality of economic outcome may want to donate more to those who suffer a heavier loss for they infer a higher marginal return of donation. So would those who believe that every patient should have equal access to necessary medical treatment, and to help reach a larger donation amount they feel obliged to contribute more. Alternatively, the donors may believe or observe that patients reporting a higher expense are in a more severe condition, and the same amount of money spent on their treatment would bring a larger gain in quality-adjusted life years.[21]

Content Distribution Mechanism

Crowdfunding platforms in China like *Qschou* generate revenue by selling insurance to donors who saw the advertisement on the platform and charging a small fee from the recipients. If the platform seeks to attract donors with appealing campaigns and show them more frequently to potential donors, donations may concentrate among these campaigns. While this may be true, the content distribution controlled by the platform only accounts for a fraction of the total exposure a campaign receives, as spontaneous sharing on social media is the primary channel for a campaign to be known by others.

[21] But surely cases like advanced cancer may have the opposite effect.

5.3 Empirical Strategy

5.3.1 Main Specification

The following transaction-level analysis aims to identify the preference channel, i.e., how recipients' academic merit and financial need determine donor generosity. By examining the within-donor variation at the transaction level, I effectively exclude the impact of the social capital disparity resulting from donor composition. By controlling for a battery of observables, I minimize the confounding effect of writing ability, illness severity, and fundraising behaviors. I also trimmed the sample based on social distance measures to exclude donations from strong ties.

$$Y_{ic} = \alpha + \beta_1 \cdot Rank_c + \beta_2 \cdot Postgrad_c + \beta_3 \cdot Expense_c + \mathbf{X_c}\Gamma_1 + \mathbf{Z_{ic}}\Gamma_2 + \mu_i + \epsilon \qquad \text{(R1)}$$

Equation (R1) presents the baseline specification. The outcome variable is the donation amount from donor i to campaign c. Academic merit is measured by *Rank*, which is constructed from raw college rank between 1-800 and rescaled to $[-8, -0.01]$ to denote selectivity, with -0.01 corresponding to the top college. Campaigns related to unranked colleges are dropped. In alternative specifications, *Rank* is replaced by a set of dummies indicating rank brackets to allow for any potential non-linearity, and campaigns related to unranked colleges are included as the reference group.[22] *Postgrad* indicates the patient or fundraiser has or is pursuing a graduate degree. For a fraction of campaigns where both undergraduate and postgraduate institutions are reported, the *Rank* corresponds to that of undergraduate institutions. The other variable of interest is the amount of medical expenses or debt mentioned, which also serves to control illness severity when examining the rank effect. The amount of expenses is winsorized at CNY 1 million (top 1.4 %). The value of variable *Expense* is set to zero if not reported, accompanied by a dummy indicating missing value.

Vector $\mathbf{X_c}$ denotes campaign-level controls and $\mathbf{Z_{ic}}$ denotes donation-level controls. The basic campaign-level controls capture the substantive content mentioned, including illness category, patient's home province, per capita GDP of the college's province, fundraiser-patient relationship, and graduation status. I constructed a categorical variable that identifies 39 types of illness, including two categories for miscellaneous and complex ones. Cancers, kidney failure, injuries from accidents, and other chronic diseases and acute injuries comprise most of my sample. 85.8% of fundraisers reported home province. Fundraiser-patient relationship takes two values in the young patient sample, narrated by the patient herself or a peer.

Additional controls on content include patient demographics, major and year of school, and campaigning behavior like initial fundraising target, number of additional content updates, and number of photos uploaded. Patient demographics include age, gender, major, and year in college. The last group of controls concerns textual characteristics, which include story length, writing quality score, grammar error density, coverage of content aspects, and

[22] Rank brackets have incremental width, namely, 1-30, 31-100, 101-200, 201-400, 401-800.

linguistic attributes like word positivity. These control variables help address concerns on selection into the platform and reporting the college name.

A donor (account) is uniquely identified by username and web address of the avatar.[23] 83.7% of the donations are linked to an identified donor in the two main campaign groups. A donor is unidentifiable if she donated anonymously or used a default avatar plus a common username. By incorporating donor fixed effects, the estimations rely on approximately 8% of the transactions from repeat donors who donated to at least two campaigns in the corresponding sample groups. Donation amount from repeat donors has a similar distribution to that of non-repeat donors. Around 82% of the repeat donors are observed twice in my main sample, the others are observed three times or more. They contributed to 2.28 campaigns on average.

A within-donor specification requires observing donations from the same donor across campaigns, which is more likely when observing a large number of campaigns. When the number of campaigns in my sample decreases linearly, the effective number of observations (donations) decreases faster than linearly. To guarantee sample size, observations with missing values in covariates are not dropped. Unreported cases are set to zero for continuous variables and accompanied by an indicator of their missing status. For categorical variables, missing values are grouped into a category indicating information not mentioned.

5.3.2 Tie Strength

Social distance is crucial to generosity. Leider et al. (2009) finds in an experiment that subjects give 52% more money to friends than to random strangers. Socially closed donors may also know information about the recipient not shown on the fundraising page. Donors are often personally connected to recipients on crowdfunding platforms. Therefore, a repeat donor may be socially closer to some recipients and donate more generously. If donations to a patient attending a more selective institution are more often between close social ties, it alone could drive the rank effect.[24]

Tie strength is not directly observed in my data, but I made two efforts to mitigate its impact. First, I trimmed the sample by excluding donations plausibly from strong ties. This includes 15% of observations when we observe a donor makes multiple donations to the same campaign, the donor leaves a comment, or keywords indicating strong ties found in fundraisers' comments.[25] These indicators of strong ties are correlated with a higher donation amount. Donations larger than CNY 300 (USD 42), or the top 2.2%, are dropped for being likely from closed ones or non-individuals. Second, I flexibly control for the sequence of donations. This helps because the donation request spreads to the socially close ones first, thus tie strength is partly accounted for by controlling the donation sequence.

[23] Identification of individual donors is validated by their current user contribution level as of July 2022. The donor contribution level is determined by the cumulative amount and times of donation, which should be invariant within a donor account.

[24] One possible scenario for social ties to contribute to the rank effect is as follows: a donor enters the platform to donate to a friend who attends a high-ranked college. Due to her higher income or other reasons, she is more likely to stay on the platform and continue to donate (a smaller amount) to other campaigns.

[25] words like classmates, college, friends, "I am..."

One might still concern the remaining impact of tie strength. Therefore, I measured the correlation between college selectivity and indicators of strong tie mentioned above. As shown in Appendix Table A1, repeat donors typically have stronger ties with campaigns related to *lower*-ranked colleges. Within donor, the donations to a campaign related to *lower*-ranked colleges are more likely to repeat within the campaign, be among the earlier donations received by a campaign, be the earlier campaigns that the donor contributes to on the platform, include a comment from the donor. As a result, any college rank effect found within the donor is dampened by tie strength.

5.4 Main Results

Attending a higher-ranked college, having a postgraduate degree, and mentioning higher expenses all lead to greater donor generosity towards a young patient, as shown in Table 5. Columns (1) and (2) of the table are estimated with full samples without donor fixed effects, column (3) does not incorporate donor fixed effects but uses the subsample of repeat donors, while columns (4) - (7) are estimated with donor fixed effects. The coefficient on *Rank* in column (3) is close to that of column (1), showing that the decrease in coefficient size when incorporating donor fixed effects does not come from the change in donor composition.

According to the preferred specification of column (7), a patient attending a top college would receive 1.48 CNY more from each donor than that related to a college ranked 500th. This equals 14.8% of the median donation or 5.2% of the mean. Reporting having a postgraduate degree yields a bonus of half that size. The effect of the amount of expenses mentioned is smaller than that of college rank. A campaign reporting spending CNY 1 million (100 percentile) would receive CNY 0.4 more than campaigns mentioning an expense of 200,000 (60 percentile).

The college rank effect (the coefficient on *Rank*) decreases by more than two-thirds after adding donor fixed effects, suggesting that social capital indeed contributes to the differential fundraising outcomes. It decreased by another 9% after controlling for content and textual characteristics, and that on *postgraduate* by 24%. There is also a decrease in the need effect (the coefficient on expenses) along the way I add controls. The need effect drops by 27% and becomes statistically insignificant after adding textual controls, which suggests fundraisers facing more severe medical conditions may have exerted more effort in writing the story and mentioned a higher expense at the same time.

There is no guarantee that the effect of academic merit should be linear in college rank. Figure 9 and Figure 10 use the same specification as columns (2) and (7) in Table 5, except for replacing the continuous rank measure with rank brackets and including the campaigns related to unranked colleges as the reference group. Comparing the two figures, we can see that adding the donor fixed effects changes the size of the coefficient but not the shape of the profile. In Figure 10, where the donor fixed effects are included, the college rank effect is more pronounced for the top 100 colleges, which account for approximately 5% of national college enrollment each year. The gradient becomes flatter for colleges beyond 200, indicating very little bonus for those who attend them. The shape of the gradient may be driven by information (people know more about top colleges) or preference (people only associate merit with top colleges).

The rank effect I estimate above tends to be a lower bound for donor preference for merit. First, tie strength is on average stronger in a donation to a patient attending a lower-ranked college, diminishing the rank effect. Second, I observe the donor's choice when a donation is made, but not when a potential donor decides not to give after viewing the page. This would likely bias my coefficient downwards, as it reduces the variation in the outcome variable that can be captured in any coefficient. Third, I mainly exploit the variation in the intensive margin within the same donor. However, attracting more donors and getting donations from more generous donors should be an important source of variation in the outcome. In fact, donors in the sample often repeat the donation amount across campaigns (e.g., giving mostly 10 yuan, but occasionally 20 yuan), which further attenuates the estimated effects. As evidence, although the effect of mentioned expenses is less likely to be driven by the disparity in social capital, the effect still decreased by approximately 65% after adding donor fixed effects. The only likely factor that may contribute to the rank effect on top of donor preference is the fundraiser ability not observed or not fully controlled.

5.5 Results from For-senior Sample

I apply the same specifications to the sample in which college students fundraise for their senior family members. The college-rank effect in the for-senior sample has different implications, as the academic merit belongs to the fundraiser instead of the patient.

As shown in Table 6 and Figure 10, a slightly smaller rank effect is found when a college-attending young adult fundraises for a senior family member. The coefficient for the fundraiser attending a postgraduate program is close to zero. Besides, the coefficient on the mentioned expense seems to be larger than that for the young patient when estimated with all controls. However, an F-test can not reject that the difference in coefficients on variables of interest between two sample groups is zero. The results are almost identical when using the log of donation amount as the dependent variable instead.

There are two possible explanations for the similar results from the two sample groups. One is that the merit effects from both groups are driven by residual ability not fully controlled. However, if this is the case, we would expect a larger effect in the for-senior group. This is because all the fundraisers in the for-senior sample attend(ed) the mentioned college, while around 44% of the fundraisers in the young patient sample is another young adult whose college attendance is not reported. The alternative explanation is that donors have similar responses to the merit of a fundraiser and to that of a patient. Donors may infer that the illness of a family member would burden the student financially and prevent them from achieving their full academic potential, as is sometimes explicitly mentioned or implicitly implied in the story. Or they might think that patients with high-achieving offspring are themselves high achievers or good nurturers, thus deserving more help. Donors might also believe that a recipient family with members attending selective colleges can make better use of the money donated to them.

5.6 Fundraising Abilities

Admission selection and college education lead to higher fundraising ability. As shown in Figure 8, writing quality measures are positively correlated with college selectivity. Writing matters to the fundraising outcome since the story is the most informative component of the campaign, and a well-written story also signals the recipient's worthiness.

The text length turns out to be the most consequential aspect of writing. A detailed story demonstrates that the fundraiser takes the campaign seriously and persuades the donors that the campaign is credible and the family is in urgent need. As shown in the last column of Table 5 and Table 6, a repeat donor donates more to campaigns with longer stories, controlling for all covariates on story components and campaign characteristics. One standard deviation increase (480 characters more) would help get CNY 0.74 more from a repeat donor for the young patient sample, or 7.4% of the median, and a smaller CNY 0.41 for the senior patient. Writing quality score is correlated with transaction level outcome before controlling for donor fixed effects, but not after. Other language characteristics like sentiment or grammar error density do not have sizeable or consistent effects once story length is controlled.

Fundraisers attending more selective colleges can be more social media savvy or write stories in a more compelling way that is not captured by my measures on writing. To test the effect of unobserved ability formally. I focus on the young patient group and interact variables of interest with an indicator for fundraising for oneself (as opposed to being fundraised by a peer). The idea is to have the interaction term to capture the fundraising ability associated with the college selectivity of the fundraiser while controlling for the patient's credentials and characteristics. The results in Table A3 does not provide strong support for the hypothesis that fundraising ability drives the rank effect, with only the last column supporting a differential effect between the two groups. However, it could be the case that the fundraisers who are socially close to the patient are as capable as the patient themselves in fundraising. Therefore, this result does not completely rule out the potential effect of ability on fundraising either.[26]

5.7 Knowledge of College Ranking

A merit-oriented donor needs to first know about the college selectivity to base donation decisions on it. People know more about local colleges than distant ones, and this information gap can be exploited to provide evidence on the donor preference channel.

[26]One suggestive evidence of writing ability comes from the fact that fundraisers who major in liberal arts and social science receive slightly more than students majoring in science and engineering. However, this effect is not robust across specifications.

In China, college admission is administered at the provincial level. 65% of the students go to college in their home province in 2021, and the number is 75% college in my main sample. People often learn about a college from acquaintances attending it, so it is natural that one would hear more about in-province colleges and have a better knowledge of their selectivity. As evidence, Eble and Hu (2022) found name-changing colleges in China enroll higher-aptitude students, with larger effects among out-of-province applicants who possess less information on college quality.

People also tend to know more about the more selective colleges, which helps explain why the rank effect is more pronounced among the top colleges. In the U.S. setting, Meyer et al. (2017) estimated that applications discontinuously drop by 2%–6% when the rank moves from inside the top 50 to outside due to limited attention to higher education rankings. These information gaps are confirmed in a quiz on college ranking in my survey experiment. As shown in Table 17, the probability of correctly selecting the rank bracket is 16% standard deviation higher for colleges in respondents' province of residence. The answer accuracy is also higher for the more selective colleges. Notably, employers in both China and the U.S. use the names of educational institutions to infer the productivity of job applicants (Eble and Hu, 2022; Clinton, 2020).

$$\begin{aligned} Y_{ic} = \alpha + \beta_0 \cdot Rank_c + \beta_1 \cdot Rank_c \times OutProv_c + \beta_2 \cdot Postgrad_c + \beta_3 \cdot Postgrad_c \times OutProv_c \\ + \beta_4 \cdot Expense_c + \beta_5 \cdot Expense_c \times OutProv_c + \beta_6 \cdot OutProv_c + \mathbf{X_c}\Gamma_1 + \mathbf{Z_{ic}}\Gamma_2 + \mu_i + \epsilon \end{aligned} \tag{R2}$$

In regression (R2), I introduce interaction terms between variables of interest and an indicator for attending college out-of-province. In alternative specifications, the distance between the recipient's home province and the college is used instead of $Outprov$. Several mild assumptions are required for the coefficient on interactions, β_1 and β_3, to help identify the donor preference channel.

First, whether a recipient attends a college (of comparable selectivity) in-province or out-of-province should not correlate with fundraising ability once we control for college ranking. Second, a repeat donor's home province substantially correlates with the recipient's home province. Therefore, attending college out-of-province, on average, decreases the familiarity regarding the college among donors. While the home province of a donor is not observed, I document that within a repeat donor, the variation in the recipients' home province is small. This suggests repeat donors more frequently donate to individuals residing in their own province. Third, attending college outside one's home province does not affect the average tie strength between a repeat donor and the recipient. This assumption may not hold if the college (location) choice alters the donor composition or the donors exhibit in-group preferences, favoring those living closer to them.

Table 7 reports the results. Among young patients, the college rank effect is almost entirely driven by recipients attending in-province colleges. This indicates attending an out-of-province college would lower donors' generosity towards the patients due to reduced college recognition among donors unfamiliar with out-of-province institutions. On the other hand, for the fundraising-for-senior sample in Table 8, the overall effect on the fundraiser's college rank does not vary with in-province status, which suggests a smaller role of the preference channel when the merit does not belong to the patient.

In-group favoritism can also lead to a stronger reaction to college rank for recipients from local colleges if donors find attending college far away makes a recipient socially distant. However, it can hardly justify the fact that attending a postgraduate program out-of-province does not compromise its bonus for young patients. The education level (graduate degree vs. bachelor's degree) is explicitly mentioned in the story and, therefore, requires no prior knowledge to appreciate and incorporate it into donation decisions. Taken together, the above results suggest donors believe that more talented people deserve more help when facing health shocks. Quantifying the exact magnitude of this preference for merit remains a challenge due to the following reasons: 1) we don't know the magnitude of the donor's information gap between in-province and out-of-province colleges, 2) the distribution of college rank varies between in-province and out-of-province samples, and if combining with non-linearity of rank effect, it may affect the size of coefficient we observed.

5.8 Donor Preference for Age

The within-donor specification can identify donor preferences beyond merit and need, and I find donors favor young patients over senior patients with comparable family backgrounds. In Table 9, I pool the sample in which a young patient fundraises either for herself or a senior family member. In other words, I combine the two main sample groups but excluded the cases in which the fundraiser's college attendance is not known.

I interact variables of interest with an indicator of the patient being the young adult herself. The main effect of *YoungPatient* captures patient age (group) variation, while *Rank* and the interaction between *Rank* and *YoungPatient* account for any differential effects of college selectivity on donor generosity. In column (3), I further excluded all graduated fundraisers to make the sample more homogeneous, a luxury I wouldn't have without pooling sample groups.

There is a strong preference for helping younger patients, which is consistent with the public health research that found people prioritize young people when medical resources are scarce (Lewis and Charny, 1989; Eisenberg et al., 2011; Reckers-Droog et al., 2018). At the campaign level, aggregate donations to young patients are more than twice those to seniors on average in our main sample. At the transaction level, a repeat donor gives CNY 1.3-2.5 (13-25% of the median) more to a young patient. This provides another solid evidence that donors are impact-seeking and implicitly maximize the social return of their donations by taking life years saved into account (Petrou et al., 2013).

In addition, we consistently observe that donors react more to college rank when donating to young patients. Unobserved fundraising ability should be captured by the main effect of college rank. The interaction terms, ranging from 31% to 54% of the overall effect among young patients, indicate a donor responds more to the patient's educational credentials than that of the fundraisers. A similar pattern is found for attending a postgraduate program. The preferred explanation is that donors associate worthiness with both fundraisers' and patients' academic credentials, but more so for the patients' credentials because saving a high-achiever from a life-threatening illness is perceived to be more impactful. However, due to a smaller number of campaigns of self-fundraising young patients, these results are not always precisely estimated.

5.9 Discussions

The results on college rank are robust to the following specification choices. 1) Using alternative cutoffs between CNY 100-1,000 of dropping a donation, a lower cutoff slightly attenuates the rank gradient. 2) Using the log of donation as the outcome variable. 3) Using the national college ranking of 2019 instead of 2022. 4) Controlling for university type (comprehensive, science & tech, the others). 5) Controlling for college province fixed effects (instead of just GDP per capita of the province). 6) Controlling for the average amount of five previous donations, the rank effect decreased by around 15% (Smith et al., 2015). Also, in line with the survey results in the later sections, there is no effect on the patient sex.

6 Experiment Design

This section introduces the design of the online survey experiment, which corroborates the observational results in several ways. First, it provides causal evidence that donors are more generous towards patients who have merit and are in need. The observational results provide evidence on both the merit and need effect but one might still have concerns about the confounding effect of residual ability or other unobserved characteristics. Second, an experiment allows for examining donor (respondent) heterogeneity, which is not feasible previously as donor characteristics are not observed on campaign pages. Importantly, the experiment results confirm that adequate knowledge of college rankings is a prerequisite for donors to respond to college selectivity. I also show that graduation from college would reduce the college selectivity bonus, as recipient deservingness is less associated with college attendance after graduation.

The online survey follows the design of prominent resume audit studies (Neumark et al., 2019; Deming et al., 2016). I formulated sixteen synthetic vignettes based on real-life fundraising stories. In each vignette, two components are randomized at the respondent level: the college of the patient and the amount of medical expenses incurred or required. After showing each vignette, I asked respondents to report their willingness to donate to the patient directly. I incentivize the respondents to pay attention and report truthfully by associating their hypothetical responses to real-life campaigns paired with each vignette based on content similarity.

After the main part of the survey, I gathered additional information about the respondents. First, they report two story aspects that affect their donation decision the most. I then collect demographic information, including gender, age, income, profession, college attended, and past and current province of residence. Finally, to measure their familiarity with college ranking, respondents took a 10-question multiple-choice quiz regarding colleges of varying selectivity, as shown in Figure 12.

The survey is conducted via *Credamo*, a Chinese survey platform akin to *Prolific*. The platform is widely used in academic and market research. Respondents are recruited from Credamo's respondent pool. The sample was restricted to individuals aged between 18-50. Upon completing the survey and passing the attention checks, respondents received a compensation of CNY 6-8. It took an average of 14.6 minutes to complete the survey, meaning the hourly compensation is above average on the platform. To guarantee sample quality, I discarded respondents who failed any attention checks or are suspected of cheating (e.g., repeatedly submitting similar survey responses with multiple accounts for money), leaving us with a sample size of 475 for analysis.

6.1 Survey Questions

Vignettes are created based on real fundraising stories scraped from *Qschou.com*. The story is first summarized by ChatGPT, and then edited by a research assistant to achieve brevity, anonymity, realism, and readability. The college name and the amount of expenses mentioned are then replaced by randomization. Stories unsuitable for randomization are excluded (e.g. patient majors in veterinary). A vignette is typically 150-250 words in length, introducing family background, medical condition, and appealing for help.

Under each vignette, we pose the following question: *With CNY 20 on hand, how much would you be willing to donate to the patient in the above vignette?* The respondents report their willingness to donate between CNY 0-20 by scrolling a bar. Figure 11 show the sample vignette and Appendix B.1 presents the details in constructing vignettes.

The survey takes the form of a vignette study. One of the alternative approaches is a conjoint analysis where respondents are presented with two sets of patient attributes and asked to allocate a fixed sum of "money" between them. The vignette study approach has two advantages over it. First, the vignette study closely mirrors an actual donation scenario, which makes the response more likely to reflect real-world outcomes. Second, reading concise stories is more engaging than juxtaposing lists of attributes, which helps maintain respondent attention. More importantly, the succinct yet comprehensive vignette mitigates demand effects, since respondents cannot easily discern the vignette components manipulated by the researchers. Therefore, compared with a conjoint analysis design, my results are much less likely to be biased by respondents' attempts to align with perceived researcher expectations. This is crucial since the primary goal of the experiment is to show that a preference for academic merit indeed exists.

6.2 Randomization

Respondents answer each question in a random sequence. Each question presents a fixed vignette with two components independently randomized at the respondent level. Each random treatment takes three possible values, which gives us nine possible variations for each vignette.

The *merit treatment* consists of three tiers of 4-year colleges in mainland China that ranked between 3-50, 100-300, or 500-800. The top two colleges with exceptional reputations are excluded to prevent the superstar effect. A college appears only once in a questionnaire. To avoid inconsistency between college attendance and the rest of the vignettes, some educational institutions are excluded. This includes medical schools, institutions specializing in agriculture, forestry, sports, police, aviation, and those collaborating with a foreign college. By doing this, I also alleviate the concerns that respondents may infer majors, jobs, and income from college names.

The *expense treatment* consists of three brackets of expenses: CNY 150,000-300,000 / 350,000-500,000 / 600,000-800,000 (equivalent to USD 30,000-110,000). These brackets approximately equate to 0.6, 1, and 1.5 times the average expense amount mentioned in actual fundraising stories.

To achieve realism, when formulating the expense triplet, the average expense for the specific disease is taken into consideration. For costlier diseases, an amount towards the higher end of the bracket range is assigned. I also vary the wording across vignettes when mentioning the specific amount. The expense treatment is a variable of interest itself, and also serves as a benchmark to assess the size of the college tier effect.

Randomization is implemented on the survey platform. Each respondent encounters one treatment pair out of nine possibilities in each question. Although the platform does not ensure an even sample size across arms, treatments assigned are not too unbalanced when pooling all questions. A total of 26%, 33%, and 41% questions are assigned with a college in tier 1, tier 2, or tier 3, respectively.

6.3 Incentives

An incentive scheme a la Kessler et al. (2019) is implemented to enhance attention and induce truthful reporting. Participants are informed that if they donate more to vignette A than to vignette B, real-life fundraisers with attributes similar to vignette A would receive more donations than those resembling vignette B.

More specifically, I pledge CNY 1000 (USD 130) to actual patients. After the experiment concludes, I will select 30-50 ongoing campaigns related to college students. Each synthetic summary from my survey will then be paired with a real-world campaign based on content similarity. Donations will be made to these matched campaigns in alignment with the proportions indicated by survey respondents for the corresponding synthetic profiles.[27]

[27]The exact wording is as follows, "*I pledge CNY 1000 to actual patients based on your and others' responses in the survey. After the RCT concludes, I will select 30-50 ongoing campaigns related to college students. Each synthetic vignette from this survey will then be paired with a real-world campaign based on content similarity. If they donate more to vignette A than to vignette B, real-life fundraisers with attributes similar to vignette A would receive more donations than those resembling vignette B.*"

6.4 Response Quality and Sample Representativeness

Response reliability is crucial for research conducted on online survey platforms. The two main concerns are hasty or inattentive responses and responses generated or assisted by computer programs that aim to monetize the survey. To address these concerns, I employed platform services including user identity confirmation and geographic restriction. I also designed attention checks to identify sloppy responses. In addition, I excluded responses apparently generated or assisted by computer programs ("Bots") and those suspicious of being submitted by "Farmers" who deploy server farms to circumvent the location restrictions of the platform and respond in bulk and repeatedly. See subsection B.2 for exclusion criteria and a detailed discussion. I received more than 900 responses but ended up excluding a substantial part of them to ensure the quality of the response.[28]

The respondents are young and well-educated (See Table 10). In the final sample, 57.7% are female. The median age bracket is 26-29, and 71.8% of the respondents are between 22 and 34 years old (with a recruitment restriction of an age between 18 and 50). The students constitute 17.1% of the respondents. The median income bracket for non-student respondents is CNY 7,500-10,000. 89.4% of the respondents report an education level of a 4-year college or higher, with current students included. The self-reported education level is presumably higher than the population average and the users of crowdfunding platforms. However, there seems to be a tendency for respondents to overstate their income and educational level, possibly as a tactic to avoid rejection by surveyors.[29]

6.5 Determinants of Donor Generosity

I collect information on subjective criteria that determine the intentional amount of donation. First, I posed an open-ended question, asking respondents to list the two most important story characteristics that affect their donation choices. Frequently mentioned factors included the severity of the illness, financial situation, and patient's age. Notably, respondents expressed impact-seeking consideration. Some claimed that they would give more to patients from a single-child family, as they are the sole pillar of support for their parents. Some mentioned that they would give more if the illness is more curable. Some view the patient's role in the family or society and the urgency of the medical need as pivotal.

Following the open-ended question, respondents report on a four-point scale how much weight they give to nine predefined aspects. As shown in Figure 13, the aspects receiving the highest importance ratings are story credibility, severity of illness, and family's financial status. Aspects associated with merit, including individual qualities and abilities, education level, and college tier, are given moderate weight. The gender and hometown of the recipient are reportedly not important in deciding how much to give.

[28]The coefficient are attenuated by roughly 26% if applying more lenient exclusion criteria instead.

[29]Surveyors are entitled to decline compensation to up to 30% of invalid or sloppy responses received on Credamo. And some market survey targets college-educated respondents.

6.6 Knowledge of College Ranking

At the end of the survey, each respondent answers a quiz that measures their knowledge of college rankings. In each multiple-choice question, I ask them to select the correct rank bracket for a college. Each respondent answers a set of 10 questions randomly drawn from 4 sets of questions. The colleges appearing in the quiz vary in selectivity and only four-year public institution is included. There are five options for each question, namely, 1-50, 50-100, 100-200, 200-400, and 400-800. On average, respondents answered 45% of the questions correctly. Based on the accuracy of responses within each quiz set, I calculate a standardized score based on the total distance between the true rank brackets of colleges and the respondents' perceptions.

Table 17 shows that the answer accuracy increases monotonically with college selectivity across the first four tiers. The answer accuracy of the top 50 colleges is 26% higher than that of colleges ranked between 201-400. This confirms that more selective colleges are better known, which is likely because the production and consumption of college quality information bias to the top ones (Meyer et al., 2017; Bowman and Bastedo, 2009). Another reason is that the rank of more selective colleges can often be inferred from their names. For example, institutions named after a province or a big city are typically flagship universities, helping respondents choose their rank bracket correctly without prior knowledge of their selectivity.

Other naming patterns also reveal colleges' selectivity. For institutions ranked 400-800, which serves as the reference group in Table 17, the answer accuracy is as high as that for colleges ranked 50-100. This is largely because these institutions are much more frequently named "college" (*xueyuan*) as opposed to "university" (*daxue*) than those in higher brackets, making it easier for the respondent to correctly assign them to the bottom bracket without any prior knowledge.[30]

7 Experiment Results

7.1 Main Results

Equation (E1) illustrates the main specification, where i denotes participant, q denotes question/vignette, k denotes three college tiers or high, medium, or low expenses mentioned. γ, δ denotes the vignette fixed effects and respondent fixed effects. In some specifications, college province fixed effects are also incorporated. The outcome variable is the willingness to donate to randomized vignettes shown to each respondent. Standard errors are clustered at the respondent level.

[30] 81% of the institutions ranked 400-800 are named "college"(xueyuan), but the number is only 8% for institutions ranked between 1-400.

$$Y_{iq} = \alpha + \Sigma_{k=2}^{3}\beta_k^1\mathbf{1}(merit = k) + \Sigma_{k=2}^{3}\beta_k^2\mathbf{1}(need = k) + \mathbf{1}(Localcollege)_{iq} \\ + QuestionSequenceFE + CollegeProvFE + \gamma_q + \delta_i + \varepsilon_{iq} \tag{E1}$$

Overall, the coefficients of interest are in line with observational results. As shown in Table 11, a donor preference for merit is found for vignettes depicting a patient going to a top-tier college (ranked 3-50), but not for the second-tier college (ranked 100-300), relative to the third-tier college (ranked 500-800). One explanation is that people don't know much about colleges beyond the top 100. As shown in Table 17, the respondent's knowledge of college rankings decreases with ranks. Another explanation is that donors associate merit only with the most selective colleges, as graduates from less prestigious colleges in China often complain about being discriminated against when trying to advance in their careers.[31] Either way, the relative size of the college-tier effect is consistent with the convex rank gradient in observational results.

Better knowledge of the college ranking makes a difference. Columns (4) and (5) report results from the high-information sample group, defined as respondents who score at or above the median within their assigned quiz set. The coefficient on top-tier colleges for this group doubles, while the coefficient on expenses among the high-information group is roughly the same size as the full sample. Therefore, the difference in college tier effect is not likely to be driven by some respondents paying more attention to both the vignettes and the quiz.

Estimated with the full sample, the coefficient for top-tier colleges is 0.32 yuan, or 11.4% of the within-respondent standard deviation. The coefficient on high-expenses is 0.74 yuan, or 26.3% of the within-respondent standard deviation, which is relatively greater than the observational results.

Incorporating college province fixed effects drives up the coefficient for top-tier colleges by around one-third, and people tend to donate more to students attending college in megacities like Beijing, Shanghai, and Tianjin.[32] This suggests that donors with limited information infer college quality from its location, which is usually mentioned in its name. This pattern is consistent with MacLeod and Urquiola (2015), where reputational concerns arise when graduates use their college of origin to signal their ability, leading to stratification in enrollment. Also, respondents donate more to someone who goes to a college in the respondent's current or past province of residence, which results from a more pronounced merit effect rather than in-group preference itself, as discussed below.

7.2 Information Heterogeneity

Knowledge of college ranking is a prerequisite for exhibiting merit preference. Individuals unfamiliar with college ranking are unable to base donations on it, even if they indeed

[31] Source: https://www.thepaper.cn/tag/380465

[32] and also the northeastern provinces

value the academic merit of the recipients.

$$\begin{aligned} Y_{iq} = \alpha + \Sigma_{k=2}^{3}\beta_k^1\mathbf{1}(merit = k) + \Sigma_{k=2}^{3}\beta_k^1\mathbf{1}(merit = k)\cdot Info + \Sigma_{k=2}^{3}\beta_k^2\mathbf{1}(need = k) \\ + \Sigma_{k=2}^{3}\beta_k^2\mathbf{1}(need = k)\cdot Info + QuestionSequenceFE + \gamma_q \ + \delta_i + \varepsilon_{iq} \end{aligned} \tag{E2}$$

I examine the information heterogeneity more formally in regression (E2), where *Info* is some variable that measures or covaries with the knowledge of rankings. Column (1) and (2) in Table 12 indicate that college tier effects are driven entirely by respondents who know college quality better. In column (1), both treatment variables are interacted with a dummy indicating half of the sample with better knowledge of the college ranking. In column (2), treatments are interacted with the score percentiles in the quiz. In both cases, the main effect for top-tier colleges diminishes to a precisely estimated zero, while the interaction effect is significant and sizable.

Columns (3) - (5) investigate the role of geographic proximity in shaping the merit effect. Given that most students attend college in-province, donors generally know much better about colleges closer to their residence. Indeed, the effect of top-tier college becomes larger when the assigned college is located in the province that the respondent currently or has lived in. Although imprecisely estimated due to the small proportion of respondent-vignette pairs in the category of *local college*, the effect of an in-province top-tier college is three times that of an out-of-province college. In addition, the donor seems to favor recipients from local second-tier colleges relative to local bottom-tier ones. The interactions of top-tier and college distance to the respondents' province of residence are negative and sizeable, which confirms that distance reduces awareness of college prestige. A top-tier college 1700km away from the respondent would bring zero merit bonus.

These results are likely to be driven by limited information on distant colleges, rather than an in-group favoritism towards recipients living close to the donors. In fact, Table 17 shows people know more about local colleges. Also, in-group preference can not explain why the main coefficient on nearby colleges is a precisely estimated zero. Nor can it explain why donors with in-group preference only respond to college-tier more but not to expenses. As shown in Table 13, the interaction effect of expense treatment and colleges being local or geographically close are precisely estimated zeros. In addition, the respondents report in the survey that, in the case of medical crowdfunding, the recipient's hometown is the least important aspect among the nine.

Although not precisely estimated, the interaction effect between second-tier colleges and information measures consistently ranges between 35% and 75% of the top-tier effect, suggesting a smaller merit effect for second-tier colleges when respondents know them better.

7.3 Preference Heterogeneity

In Table 14, I interact both treatments with vignette characteristics and respondent characteristics to understand the mechanisms underlying the preference for merit. The merit effect is mainly driven by one-third of the respondents who self-reported to be more meritocratic, defined by their answers on the subjective importance of personal qualities/ability, college tier, and education level depicted in the vignettes.

The college tier effect is 56% - 86% smaller for eight vignettes depicting a graduate instead of a current student, with their jobs usually mentioned. This pattern is consistent with the observational results in Table A4, where I employ a specification similar to Equation R2 and interact variables of interest with graduation status. On the crowdfunding platform, the average amount of donation that a graduate receives is much larger than that received by a current student. This suggests that graduates receive help from wealthier donors and attending college helps forge valuable social ties. On the other hand, college selectivity after one graduated matters *less* in shaping perceived worthiness. Columns (2) and (3) show that the overall rank effect is reduced by 30-50% for graduates, suggesting that donors give less weight to college selectivity when donating to graduated patients.

After graduation, donors may evaluate one's merit by additional aspects like occupational prestige and workplace performance. Also, the fundraiser might infer that graduates from more selective college have started earning a higher salary and should be more responsible for their medical expenses. These two justify a smaller v in Equation 5 and thus a smaller rank gradient. This pattern is later confirmed by experiment results Also, there is little differential effect for the graduates regarding financial need, which alleviates concerns for potential selection. This result on graduation status echoes Bordón and Braga (2020), who found college prestige is larger in the year a graduate enters the labor market but becomes less important later as workers reveal their quality throughout their careers.

Graduation status is not randomized in the experiment, and thus its interaction effect lacks causal interpretation. Patient's age could be a potential confounder here. In 10 of 16 vignettes, the patient's age is explicitly mentioned, and if not, it can often be inferred from the content. Graduates depicted in the vignettes are on average 7 years older than a current student. Therefore, the heterogeneity of graduation status may partly arise from respondents showing a preference for younger patients whose life trajectory is more malleable.

Interestingly, whenever merit is valued more, need is valued less, as the interaction effect for the two treatments in Table 14 always has the opposite sign. This result is predicted by Equation 6 in the model section. For a more egalitarian donor who values college rank less, and relatively values the patient's health more, we have a larger V_0 (donor's weight on saving a life regardless of individual merit) relative to v (public perception on merit), which leads to a decrease in merit gradient $\partial g/\partial m$, and an increase in shock gradient $\partial g/\partial s$. Besides, this pattern might be strengthened by a substitution effect between merit and need in capturing the reader's attention and affecting donation decisions.

Table 15 reports additional respondent heterogeneity. Being male, middle-aged, having a high income, or attending a better college is associated with a larger response to patients' merit and usually a smaller response to reported expenses. In other words, female and young respondents are found to be much more egalitarian and less meritocratic. These heterogeneities are sizable and likely to be a result of preference heterogeneity. Of course, we can not rule out the possibility that groups with high income may know more about the college rankings than others, or that the donors attending selective colleges themselves respond to recipients' education credentials due to homophily rather than meritocratic preference.

7.4 Discussions

Taken together, experimental results align with my findings from observational data, albeit with some differences in relative size. The college rank effect in the experiment, translated to comparable continuous measures and benchmarked against the financial need effect, is around one-third of that from observational results.

One explanation is that real-world donors encounter fundraising campaigns more or less connected to them, making the mentioned colleges geographically closer and more familiar to them. Whereas in the survey, respondents encounter distant colleges drawn from all over the country, making it harder for donors to base their donations on college selectivity.

Also, information on financial needs is more scarce in the experiment setting than in more detailed fundraising stories on the platform, which makes the mentioned expense more salient in donors' decision-making process. Furthermore, numeric descriptions are easier for respondents to digest than verbal descriptions. The amount of expenses can even have an unintended priming effect on reporting the amount of intentional donation. Nevertheless, the quantitative difference in the coefficient size suggests the possibility that the rank effect estimated with observational data may to some extent overestimate the donor preference channel.

There are several explanations for the donor preference for academic merit, and upcoming waves of experiments aim to disentangle them. The preferred explanation is perceived deservingness. Donors may want to reward past achievements and believe that recipients with outstanding credentials are entitled to help. Alternatively, donors may expect a greater impact from helping elite students if they could contribute more to society after the cure. In other words, donors behave like forward-looking investors who maximize social return. This also explains that donors are more generous to young patients whose lives have more potential and to whom the marginal product of donation is high.

A similar but slightly different explanation is that the better-educated are expected to manage the funds better. They may have better medical knowledge and are less likely to waste money on quack remedies. Or they are perceived to be more self-disciplined and less likely to misappropriate the donation.[33] Relatedly, Exley (2020) found participants in the experiment donate less to charities with lower performance metrics and Gneezy et al. (2014) documented a negative correlation between the amount donated to a charity and its administrative and fundraising costs.

Another explanation is credibility. Exaggeration or fraud exists in crowdfunding, and donors can be reluctant to donate to recipients without a strong connection with them.

[33]There are anecdotes about parents who raised money in the name of their ill daughter but spent the money elsewhere

The selective colleges might care more about their reputation and would manage to avoid scandals of fraudulent campaigns, in this case, donors may reasonably infer that recipients reportedly from selective colleges are more credible.

Vanity could have played a role. Giving to someone attending a renowned college associates the donor with its prestige, and thus amplifies the joy of giving. People may even react to college prestige without associating it with the recipient. It is well documented that people prefer familiar things (e.g., Home bias in stock portfolios). Therefore, donors may unconsciously donate more when the recipient mentions a college they have ever heard of, which is more likely to be a selective and local one. However, neither the credibility nor the familiarity channels can explain why donors react favorably to the recipient's educational level.

Last, self-interested donors may treat the donation as an investment in informal insurance, expecting a return of favor when in need. In this case, donors rationally invest more in those with higher potential income. This is not likely on the crowdfunding platform because donors seldom reveal their identity by leaving comments, making recognizing the username the only way for the recipients to recognize the donor, and even if they do, there are too many donations to keep track of. In addition, I have excluded donors with explicit strong ties with the recipient in the analysis. More importantly, quid pro quo can never drive the college tier effect in the experiment.

8 Conclusion

In this paper, I decompose medical crowdfunding outcome differentials into social capital disparity, variation in content, fundraising ability, and donor preference. With an experiment, I identify the donor preference for the academic merit of recipients who encountered major health and financial shocks. Knowledge of college ranking is a prerequisite for donors to respond to college selectivity, an effect driven mainly by the top colleges.

Medical crowdfunding provides crucial support to distressed families, forms a social safety net, and relieves the government of the heavy fiscal burden of poverty relief. However, those with good storytelling skills, affluent friends, and the prestige of elite college are getting the lion's share. An overconcentration of donations among a few recipients might lower the marginal product of giving. Therefore, from the perspective of a social planner, it is beneficial if we can make crowdfunding platforms more equitable for all recipients.

Education is deemed a major channel of social mobility. In China, sponsoring poor students for schooling is a prominent theme in charitable giving. Many donors believe that lifting students from poverty and supporting their pursuit of education helps promote equality and social progress. Ironically, an entrenched interest has formed based on college prestige. Blind credentialism precludes those without a (impressive) diploma from opportunities for career advancement or getting a helping hand when in distress. This breeds injustice and, in turn, explains why students compete fiercely to get into a selective college.

In many societies in Eastern Asia, meritocracy rules at schools and the workplace, and people are more efficiency-oriented than equity-minded. This creates incentives for competition and hard work, laying the ground for economic growth, but also poses a threat to social cohesion (Sandel, 2020). In the case of medical crowdfunding, a donor preference for merit could be productive, as it prioritizes recipients with higher potential productivity after cure. However, a preference for merit too strong, combined with the herding behavior of donors, can limit the chance for disadvantaged patients to receive life-saving donations that are desperately needed. This is how meritocracy harms.

Figures and Tables: Observational Data

Figure 1: Campaign Page: Story and Progress

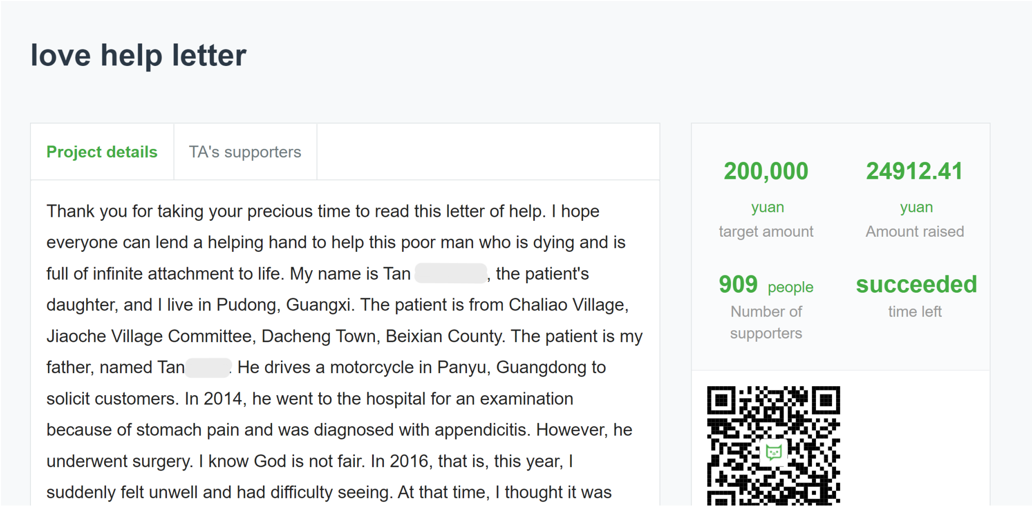


Figure 2: Campaign Page: Basic Information

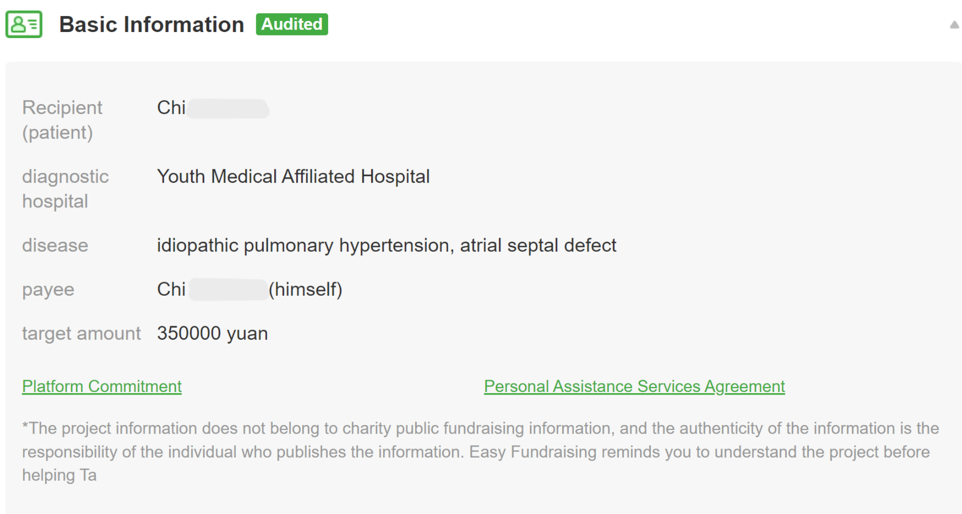


Figure 3: Campaign Page: Donation History

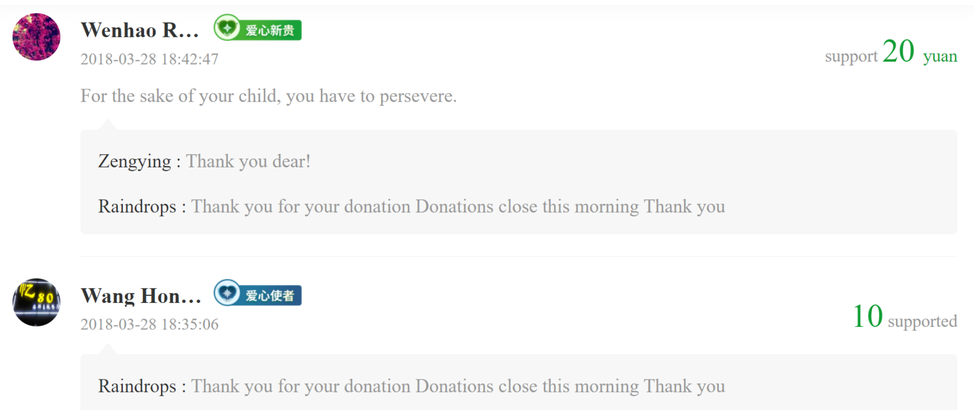


Figure 4: Outcome distribution of all 140,000 scraped campaigns

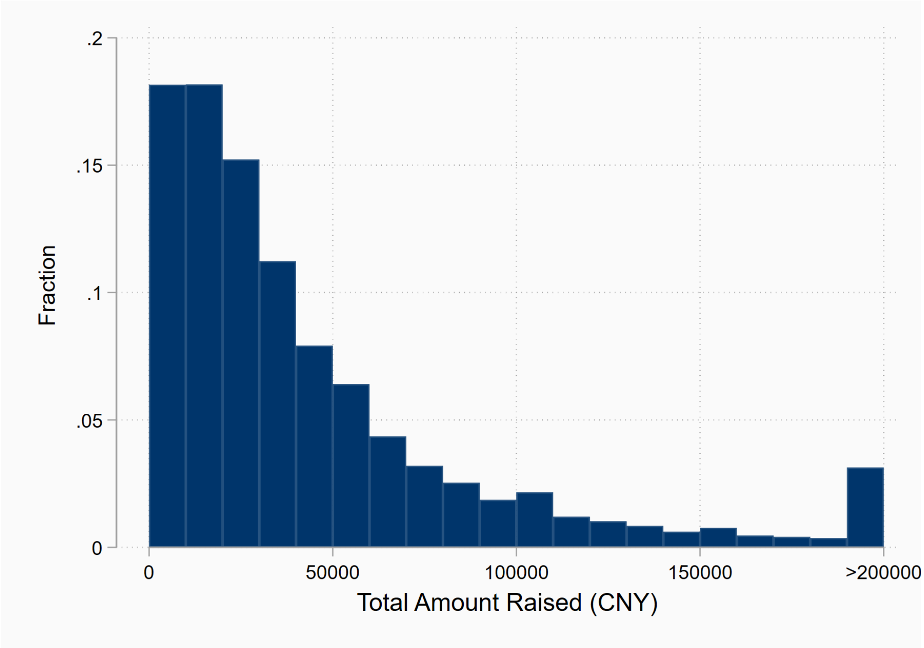
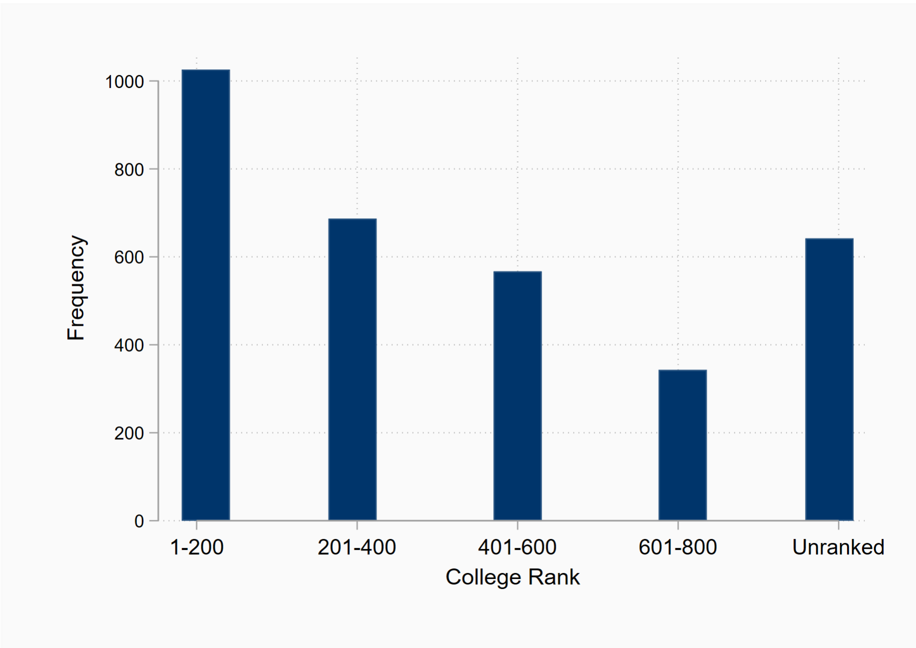
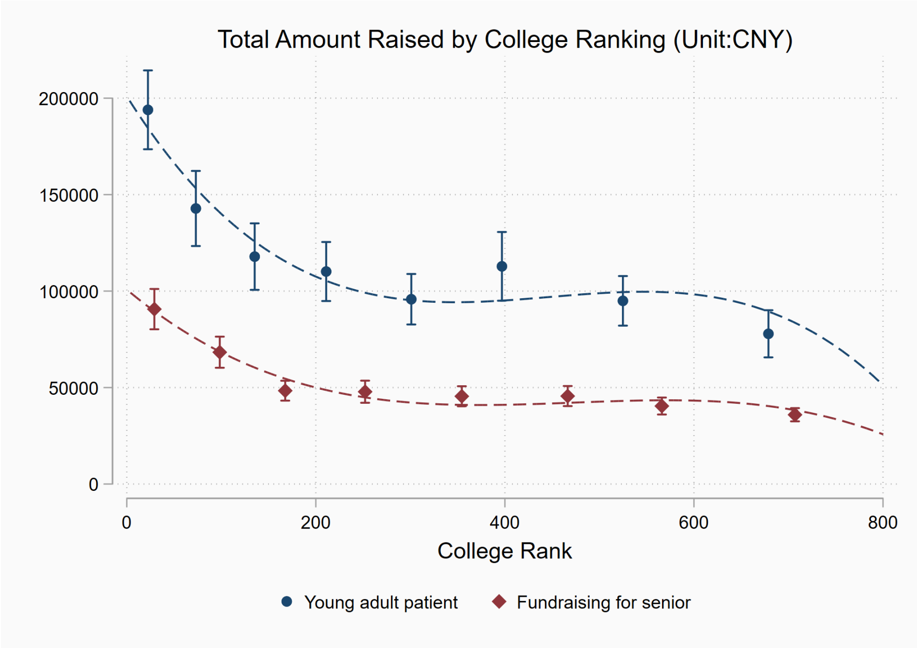


Figure 5: Distribution of the rank of college mentioned in the main sample



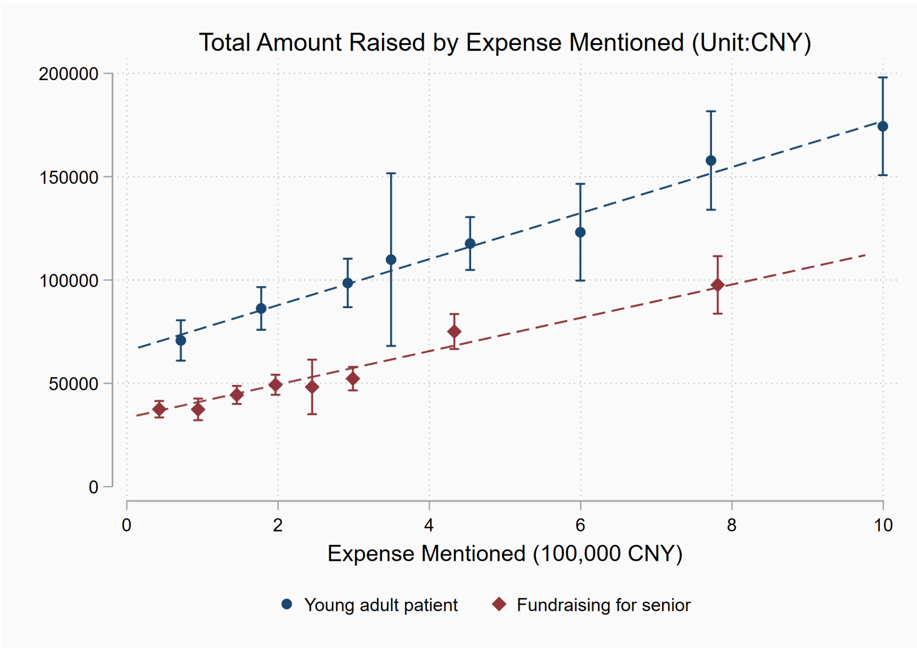
Note: Distribution of college rank in the main sample group, i.e., fundraising campaigns mentioning a college attended by either the patient or the fundraisers. The Patient is either a young adult or a senior family member. *Unranked* colleges are colleges outside the 2021 national college ranking by *Shanghai Ranking*.

Figure 6: The Rank Gradient at the Campaign Level



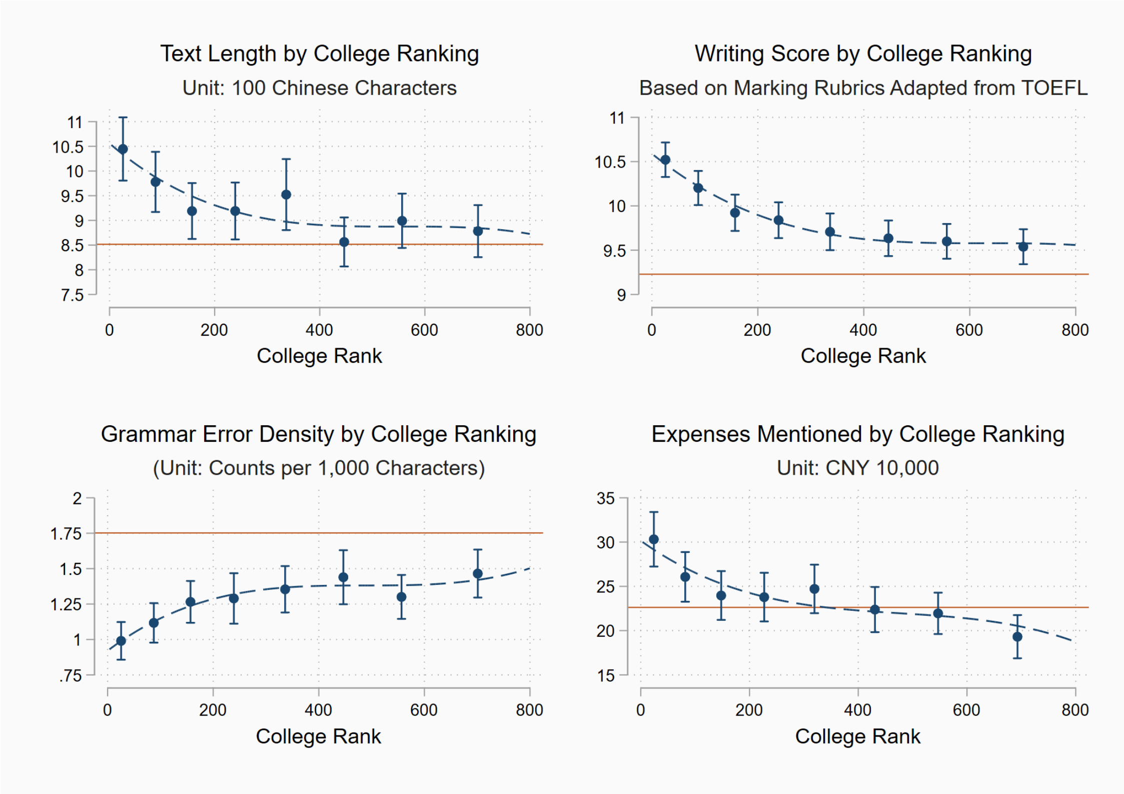
Note: Binscatter plot with no controls. Dash lines denote a cubic polynomial fit. Samples are campaigns with the recipient's college reported. The sample size is 1092 for the young-adult-patient sample and 1531 for the fundraising-for-senior sample.

Figure 7: The Expense Gradient at the Campaign Level



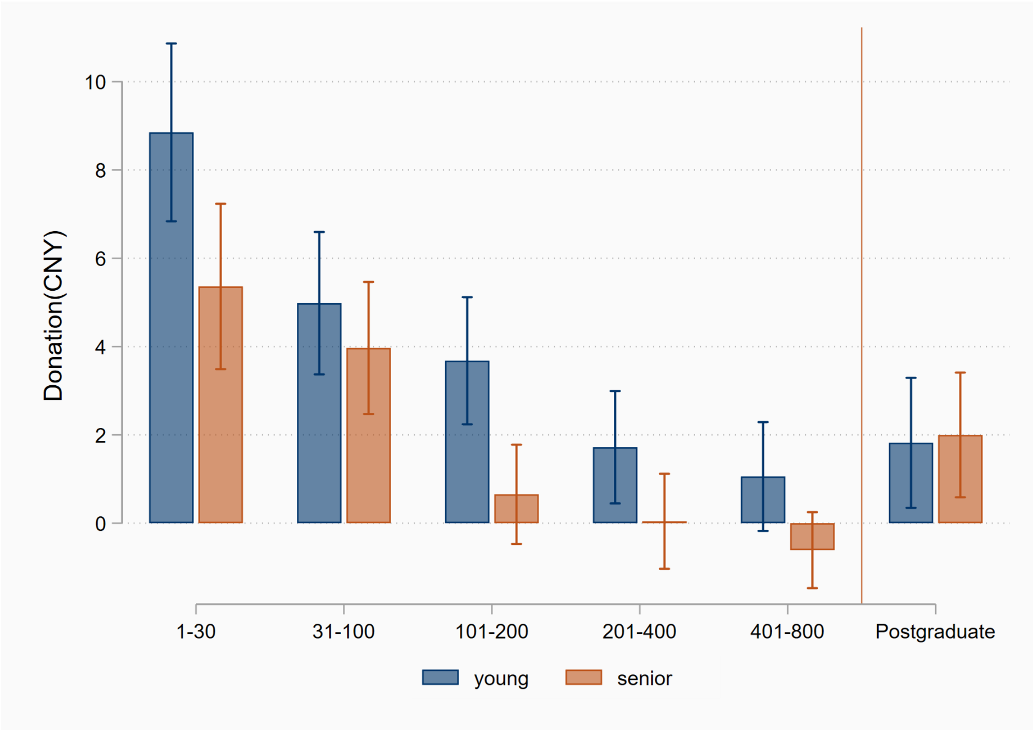
Note: Binscatter plot with no controls. Dash lines denote a linear fit. Samples are campaigns with both college and expenses reported. The sample size is 1047 for the young-adult-patient sample and 1355 for the fundraising-for-senior sample. Expenses are winsored at 1 million.

Figure 8: Writing characteristics by College Ranking



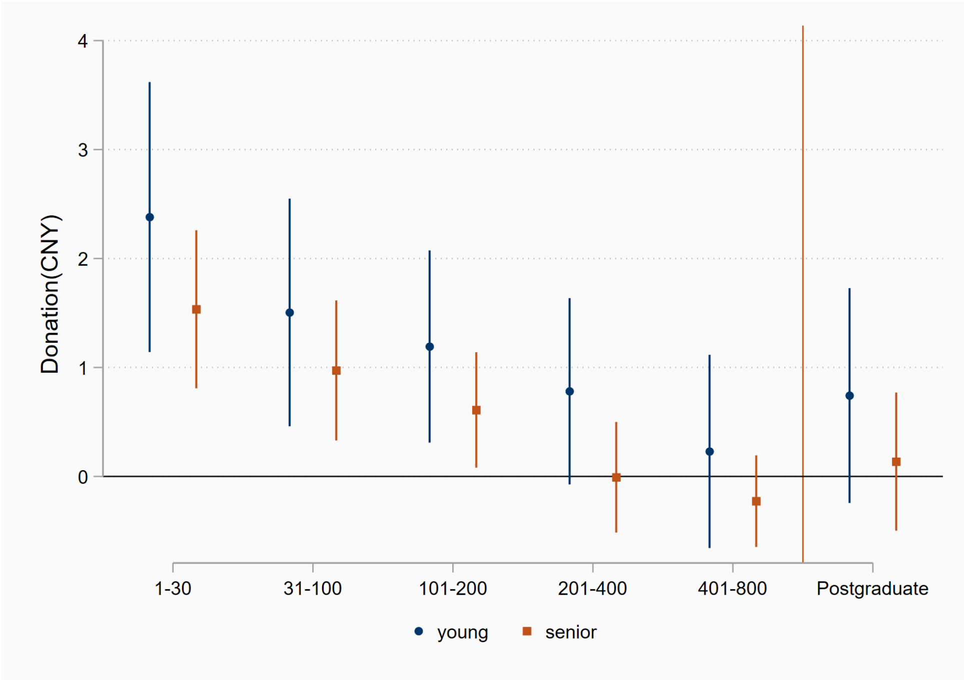
Note: Binscatter plot with no controls. Dash lines denote a cubic polynomial fit. The horizontal solid line denotes the mean for less selective colleges (unranked and independent colleges). Samples are campaigns with the college of the fundraiser(narrator) college reported. Expenses are winsored at 1 million.

Figure 9: College Rank Effect without Donor FE



Note: Coefficient plot of college rank brackets at the donation level. The reference group is unranked colleges. Donations larger than CNY 300 and those with signs of strong ties are excluded. The specification relies on the full donor sample and does not include the donor fixed effects. *Young* denotes the sample group where the patient is a young adult who attends or attended college, *Senior* denotes the campaigns where a young adult attending college fundraises for an ill senior family member. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Figure 10: College Rank Effect with Donor FE



Note: Coefficient plot of college rank brackets at the donation level. The reference group is unranked colleges. Donations larger than CNY 300 and those with signs of strong ties are excluded. The specification relies on repeat donors who are observed in multiple campaigns. *Young* denotes the sample group where the patient is a young adult who attends or attended college, *Senior* denotes the campaigns where a young adult attending college fundraises for an ill senior family member. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 3: Summary Statistics: College Premium at the Campaign Level

	Not Matched	Univ. Matched
Amount Raised	46123.6	81382.7
	(58793.7)	(103031.8)
No. of Donations	1383.7	2385.5
	(1810.2)	(2700.5)
Avg Donation	35.9	35.2
	(19.3)	(19.1)
Duration (days)	18.2	14.4
	(14.1)	(14.2)
No. of Endorsers	49.0	80.3
	(40.0)	(60.3)
Text Length	586.3	905.6
	(387.9)	(524.4)
Obs	132,350	5,687

Note. University Matched Sample includes campaigns with recipients' college (full name) reported. *Endorsers* are friends and relatives of the recipient family who vouch for the credibility of the campaign.

Table 4: Young vs. Senior Patient at the Campaign Level

Variable	Young Adult	For Senior
Amount raised	107,406	49,954
	(95811)	(45378)
No. of Donations	3,286	1,709
	(3146)	(1549)
Mean Donation	39.22	31.33
	(19.02)	(13.77)
College Rank	292.4	329.3
	(216.7)	(224.2)
Postgraduate Degree	0.09	0.09
	(0.29)	(0.28)
Medical Expenses (100K)	3.11	1.75
	(3.15)	(2.12)
Expense Unreported	0.27	0.32
	(0.45)	(0.47)
Patient Age	24.49	49.59
	(4.69)	(6.03)
Graduated	0.44	0.18
	(0.50)	(0.39)
Out-of-Prov. College	0.36	0.30
	(0.48)	(0.46)
Home-College Dist.	0.37	0.31
	(0.63)	(0.57)
Fundraising For Oneself	0.46	*N/A*
	(0.50)	
Text Length (100 Char.)	9.17	8.81
	(5.12)	(4.89)
Writing Quality	0.12	-0.06
	(1.26)	(1.10)
Grammar Error Density	1.51	1.40
	(1.72)	(1.48)
Observations	1,443	2,003

Note. Sample: campaigns with the patient or the fundraiser reporting her college. *Postgraduate Degree* indicates that the patient/fundraiser attend(ed) a postgraduate program. *Graduated* denotes the recipient has graduated from college. *Out-of-Prov. College* denotes the recipient attend(ed) out-of-province college. *Home-College Dist.* denotes 1000 kilometers between the recipient family's hometown and the college. *Medical Expenses* are the expenses mentioned in the fundraising story. *Text Length* is in units of 100 Chinese characters. *Writing Quality* is a rating provided by ChatGPT according to TOEFL-style marking rubrics. *Grammar Error Density* is in the unit of one error per 1000 Chinese characters.

Table 5: Main Specification: Young Patient Sample

	Dependent Variable: Donation Amount						
	(1) Full Sample	(2) Full Sample	(3) Rep. Donor	(4) Rep. Donor	(5) Rep. Donor	(6) Rep. Donor	(7) Rep. Donor
Rank (per #100)	1.460***	0.894***	1.553***	0.245**	0.313***	0.316***	0.293***
	(0.164)	(0.131)	(0.196)	(0.0964)	(0.0936)	(0.0907)	(0.0846)
Postgraduate	3.124***	2.574***	2.660*	0.917	1.015*	1.230**	0.865
	(1.020)	(0.746)	(1.396)	(0.660)	(0.584)	(0.568)	(0.528)
Expense Mentioned	0.302***	0.149**	0.197	0.00860	0.0863**	0.0703*	0.0513
(CNY 100K)	(0.0947)	(0.0711)	(0.120)	(0.0475)	(0.0405)	(0.0391)	(0.0338)
Text Length (100 Char.)		0.121**					0.149***
		(0.0603)					(0.0406)
Writing Score		0.190					-0.0127
		(0.166)					(0.0940)
Grammar Error Density		0.0453					0.0838
		(0.184)					(0.115)
Donor FEs	No	No	No	Yes	Yes	Yes	Yes
Basic Controls	No	Yes	No	No	Yes	Yes	Yes
Content Controls	No	Yes	No	No	No	Yes	Yes
Textual Controls	No	Yes	No	No	No	No	Yes
Adj. R-squared	0.010	0.036	0.010	0.54	0.55	0.55	0.55
Number of Obs.	2,294,122	2,294,122	193,657	193,657	193,657	193,657	193,657

Note. Sample: Campaigns for young patients with college mentioned. Unranked colleges are excluded. Donations larger than CNY 300 and those with signs of strong ties are excluded. *Rep. Donor* indicates the subsample of donations from donors observed in at least two campaigns. The median donation amount is CNY 10, and the mean is around 29. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 6: Main Specification: For Senior Sample

	Dependent Variable: Donation Amount						
	(1) Full Sample	(2) Full Sample	(3) Rep. Donor	(4) Rep. Donor	(5) Rep. Donor	(6) Rep. Donor	(7) Rep. Donor
Rank (per #100)	0.960***	0.605***	0.983***	0.242***	0.282***	0.264***	0.267***
	(0.121)	(0.0970)	(0.137)	(0.0478)	(0.0475)	(0.0470)	(0.0469)
Postgraduate	3.875***	2.749***	4.792***	0.166	0.221	0.248	0.233
	(0.807)	(0.748)	(0.926)	(0.356)	(0.339)	(0.337)	(0.345)
Expense Mentioned	0.506***	0.315***	0.370***	-0.0163	0.0668	0.0817	0.0803
(CNY 100K)	(0.112)	(0.109)	(0.140)	(0.0488)	(0.0503)	(0.0529)	(0.0522)
Text Length(100 Char.)		0.112**					0.0834***
		(0.0511)					(0.0235)
Writing Score		0.153					-0.0503
		(0.137)					(0.0581)
Grammar Error Density		0.00676					-0.0656
		(0.165)					(0.0766)
Donor FEs	No	No	No	Yes	Yes	Yes	Yes
Basic Controls	No	Yes	No	No	Yes	Yes	Yes
Content Controls	No	Yes	No	No	No	Yes	Yes
Textual Controls	No	Yes	No	No	No	No	Yes
Adj. R-squared	0.0086	0.027	0.015	0.52	0.52	0.53	0.53
Number of Obs.	1,854,746	1,854,746	145,245	145,245	145,245	145,245	145,245

Note. Sample: Campaigns for a senior family member by a young fundraiser whose college is mentioned. Unranked colleges are excluded. Donations larger than CNY 300 and those with signs of strong ties are excluded. *Rep. Donor* indicates the subsample of donations from donors observed in at least two campaigns. The median donation amount is CNY 10, and the mean is between 17 and 23. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 7: In Province vs. Out-of-Province: Young Patient Sample

	Dependent Variable: Donation Amount			
	(1)	(2)	(3)	(4)
Rank	0.248**	0.352***	0.333***	0.330***
	(0.106)	(0.103)	(0.107)	(0.105)
Rank × Out-of-prov.	-0.411*		-0.319*	
	(0.222)		(0.186)	
Rank × Home-College Dist.		-0.455***		-0.221*
(1000km)		(0.114)		(0.116)
Postgraduate	1.163	1.408	0.157	0.481
	(1.099)	(0.879)	(0.766)	(0.638)
Postgraduate × Out-of-prov.	0.134		1.256	
	(1.203)		(0.927)	
Postgraduate × Home-College Dist.		-0.307		0.693
		(0.621)		(0.597)
Out-of-prov.	0.844		0.546	
	(1.148)		(0.971)	
Home-College Distance		-1.036*		0.0354
		(0.554)		(0.629)
Donor FEs	Yes	Yes	Yes	Yes
Basic Controls	No	No	Yes	Yes
Content Controls	No	No	Yes	Yes
Textual Controls	No	No	Yes	Yes
Adj. R-squared	0.54	0.54	0.55	0.55
Number of Obs.	135,414	135,414	135,414	135,414

Note. Sample: Campaigns for young patients with college and home province mentioned. Donations larger than CNY 300 and those with signs of strong ties are excluded. *Out-of-Province* indicates the patient attends an out-of-province college. The median donation amount is CNY 10. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 8: In Province vs. Out-of-Province: For-Senior Sample

	Dependent Variable: Donation Amount			
	(1)	(2)	(3)	(4)
Rank	0.213***	0.239***	0.254***	0.247***
	(0.0607)	(0.0605)	(0.0641)	(0.0625)
Rank × Out-of-prov.	0.132		0.0111	
	(0.120)		(0.122)	
Rank × Home-College Dist.		0.0646		0.0347
(1000km)		(0.104)		(0.100)
Postgraduate	0.413	0.525	0.764	0.790
	(0.571)	(0.524)	(0.612)	(0.504)
Postgraduate × Out-of-prov.	-0.165		-0.637	
	(0.794)		(0.798)	
Postgraduate × Home-College Dist.		-0.450		-0.910
		(0.714)		(0.700)
Out-of-prov.	0.765		0.747	
	(0.595)		(0.565)	
Home-College Distance		0.126		0.597
		(0.473)		(0.454)
Donor FEs	Yes	Yes	Yes	Yes
Basic Controls	No	No	Yes	Yes
Content Controls	No	No	Yes	Yes
Textual Controls	No	No	Yes	Yes
Adj. R-squared	0.51	0.51	0.52	0.52
Number of Obs.	109,569	109,569	109,569	109,569

Note. Sample: Campaigns for senior patients with fundraiser's college and family home province mentioned. *Out-of-Province* indicates the fundraiser attends an out-of-province college. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Donations larger than CNY 300 and those with signs of strong ties are excluded. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 9: Young vs. Senior Patients

	Dependent Variable: Donation Amount			
	(1) Full Sample	(2) Repeat Donor	(3) Student Patients	(4) Log Amount
Young Patient	2.564**	1.307***	2.168***	0.0594***
	(1.130)	(0.480)	(0.608)	(0.0149)
College Rank	0.632***	0.266***	0.221***	0.01000***
	(0.102)	(0.0462)	(0.0489)	(0.00164)
Young Patient × Rank	0.262	0.121	0.273***	0.00305
	(0.200)	(0.0830)	(0.103)	(0.00276)
Postgraduate	2.773***	0.177	0.267	0.0146
	(0.754)	(0.324)	(0.378)	(0.0105)
Young Patient × Postgraduate	-0.450	0.215	0.878	0.00426
	(1.154)	(0.510)	(0.728)	(0.0157)
Expense (CNY 100K)	0.348***	0.0572	0.0403	0.00150
	(0.130)	(0.0498)	(0.0575)	(0.00176)
Young Patient × Expense	0.110	0.0293	-0.0294	0.00176
	(0.188)	(0.0774)	(0.0889)	(0.00242)
Donor FEs	No	Yes	Yes	Yes
Basic Controls	Yes	Yes	Yes	Yes
Content Controls	Yes	Yes	Yes	Yes
Textual Controls	Yes	Yes	Yes	Yes
Adj. R-squared	0.034	0.55	0.54	0.66
Number of Obs.	3,168,137	341,978	188,677	341,978

Note. Sample: Campaigns by fundraisers with college mentioned. Young patients are fundraising for themselves (i.e. excluding the cases when their peer is fundraising). The median donation amount is CNY 10. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. The exact age of the patient is not controlled. Donations larger than CNY 300 and those with signs of strong ties are excluded. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Figures and Tables: Experiment

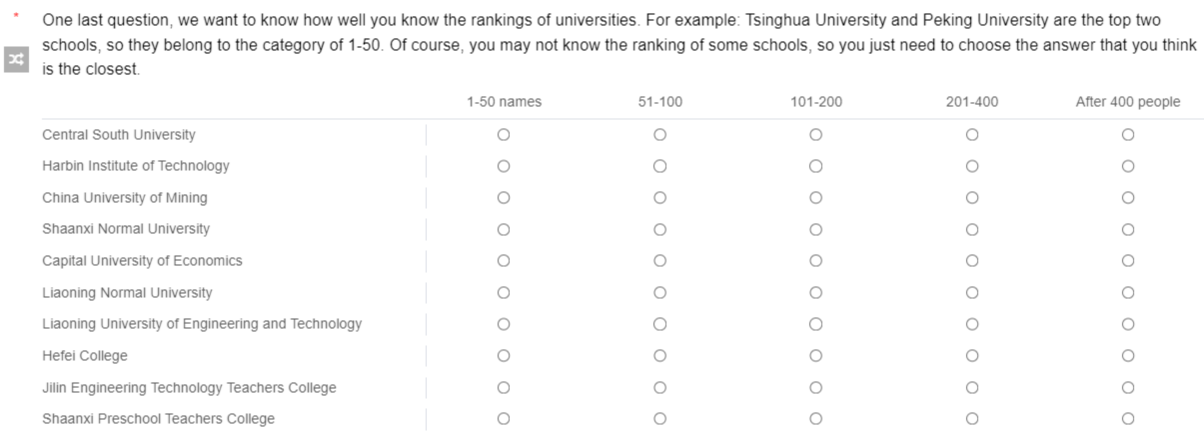
Figure 11: Sample Survey Question

Q1* Please help my brother! My brother, Zhang Feng (36 years old, graduated in 2003 with a degree in Economics and Management from [University Name]), was admitted to the Intensive Care Unit in January 2016 for treatment of aortic dissection. He spent over 100,000 yuan within three days of hospitalization. My brother used to be the hope of our entire family. He was a university graduate from a low-income household in our village. To support our family, he worked diligently and last year, he took a leap from his job and partnered with others to start his own business. However, his career was just taking off when he was struck by illness.We have already borrowed money from all our relatives and friends, but it is estimated that my brother's medical expenses will require at least [amount]. I cannot bear to see him leave us like this, and I dare not tell our elderly and frail parents about my brother's condition. Our family, in this precarious situation, truly needs the help of society. I earnestly implore everyone to extend a helping hand!

0 20

How much would you donate to this person?

Figure 12: Sample Quiz Question on College Rankings



* One last question, we want to know how well you know the rankings of universities. For example: Tsinghua University and Peking University are the top two schools, so they belong to the category of 1-50. Of course, you may not know the ranking of some schools, so you just need to choose the answer that you think is the closest.

	1-50 names	51-100	101-200	201-400	After 400 people
Central South University	○	○	○	○	○
Harbin Institute of Technology	○	○	○	○	○
China University of Mining	○	○	○	○	○
Shaanxi Normal University	○	○	○	○	○
Capital University of Economics	○	○	○	○	○
Liaoning Normal University	○	○	○	○	○
Liaoning University of Engineering and Technology	○	○	○	○	○
Hefei College	○	○	○	○	○
Jilin Engineering Technology Teachers College	○	○	○	○	○
Shaanxi Preschool Teachers College	○	○	○	○	○

Figure 13: Self-Reported Importance of Narrative Aspects

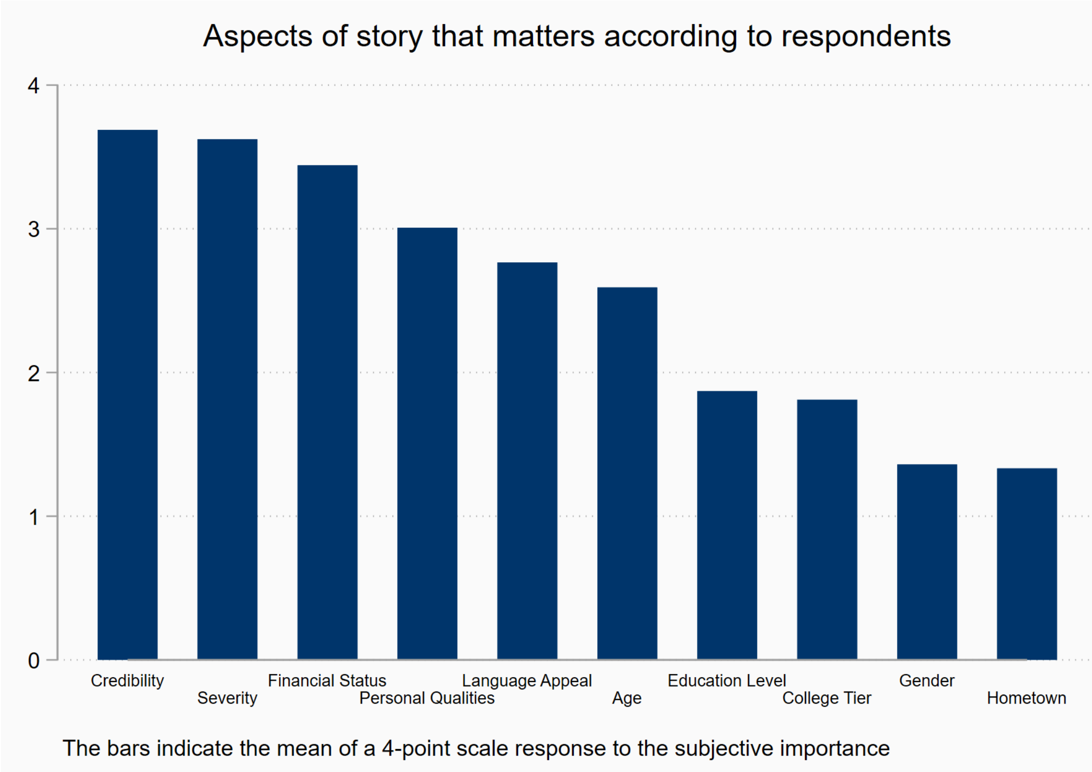


Table 10: Respondent Demographics and Response Summary

Factor	Level	Value
N		475
Average donation of respondent, mean (SD)		13.03 (3.44)
Male	0	274 (57.7%)
	1	201 (42.3%)
Age	18-21	37 (7.8%)
	22-25	95 (20.0%)
	26-29	120 (25.3%)
	30-34	126 (26.5%)
	35-39	59 (12.4%)
	40-49	38 (8.0%)
Education level	3-year college or below	50 (10.5%)
	4-year college	345 (72.6%)
	postgraduate	80 (16.8%)
Sector	Public institution	38 (8.0%)
	Gov. or state-owned	89 (18.7%)
	Foreign firms	26 (5.5%)
	Students	81 (17.1%)
	Private firms	241 (50.7%)
Income	No income	67 (14.2%)
	<5000	78 (16.5%)
	5000-7500	100 (21.2%)
	7500-10000	108 (22.9%)
	>10000	119 (25.2%)
College rank of Respondent, mean (SD)		206.33 (181.48)
Survey duration, mean (SD)		879.42 (271.23)
Col. Rank Perception (N correctly answered)		4.51 (2.13)
Col. Rank Perception (Total deviation)		-7.93 (3.89)

Table 11: RCT Main

	Dependent Variable: Willingness to Donate				
	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) High Info	(5) High Info
Top Tier	0.208**	0.247**	0.321**	0.477***	0.632***
	(0.103)	(0.101)	(0.153)	(0.136)	(0.202)
Second Tier	-0.068	-0.079	0.040	0.000	0.226
	(0.083)	(0.081)	(0.155)	(0.113)	(0.213)
High Expenses	0.717***	0.728***	0.735***	0.783***	0.801***
	(0.096)	(0.094)	(0.094)	(0.141)	(0.140)
Medium Expenses	0.363***	0.401***	0.405***	0.576***	0.587***
	(0.095)	(0.091)	(0.091)	(0.132)	(0.132)
Local College			0.221		0.557***
			(0.143)		(0.198)
Same Gender			-0.007		0.133
			(0.071)		(0.094)
Donor FEs	Yes	Yes	Yes	Yes	Yes
Vignette FEs	No	Yes	Yes	Yes	Yes
Question Sequence FEs	No	Yes	Yes	Yes	Yes
Col. Prov. FEs	No	No	Yes	No	Yes
N	7600	7600	7600	4032	4032
N_Respondent	475	475	475	252	252
Adjusted r^2	0.576	0.609	0.610	0.600	0.602

Note. The outcome variable is the response to fundraising vignettes where patients' college and medical expenses are independently randomized. The reference group is the bottom-tier colleges and low expenses mentioned. The outcome variable takes a value between 0 and 20, and the within-respondent standard deviation is 2.81. The *High Info* sample group is defined as 53% of respondents who score at or above the median within their assigned set of quiz on college rankings. *Local College* denotes that the assigned college is located in the province of residence of the respondent. Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 12: RCT: Heterogeneity in Ranking Perception

	D.V.: Willingness to Donate			
	(1)	(2)	(3)	(4)
TopTier	0.015	-0.025	0.216**	0.542***
	(0.147)	(0.189)	(0.102)	(0.186)
SecondTier	-0.168	-0.163	-0.096	-0.049
	(0.117)	(0.155)	(0.084)	(0.162)
High Info × *TopTier*	0.444**			
	(0.199)			
High Info × *SecondTier*	0.175			
	(0.163)			
Quiz Pctl × *TopTier*		0.578*		
		(0.321)		
Quiz Pctl × *SecondTier*		0.184		
		(0.282)		
Local College			0.060	
			(0.265)	
Local College × *TopTier*			0.423	
			(0.340)	
Local College × *SecondTier*			0.321	
			(0.347)	
Home-College Dist.				0.084
				(0.123)
Home-College Dist. × *TopTier*				-0.324*
				(0.167)
Home-College Dist. × *SecondTier*				-0.031
				(0.154)
Respondent FE, Vignette FE, & Question Sequence FE	Yes	Yes	Yes	Yes
Expenses Treatment & Interactions	Yes	Yes	Yes	Yes
N	7600	7600	7600	7600
N_Respondent	475	475	475	475
Adj. R-squared	0.609	0.609	0.609	0.609

Note. The outcome variable is the response to fundraising vignettes where patients' college and medical expenses are independently randomized. The reference group is the bottom-tier colleges and low expenses mentioned. The outcome variable takes a value between 0 and 20, and the within-respondent standard deviation is 2.81. *High Info* is defined as 53% of the respondents scoring at or above the median within their assigned quiz question sets on college rankings. *Quiz Pctl* is respondents' score percentiles from the quiz on college rankings. *Local College* denotes colleges in respondents' current or previous province of residence. Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 13: RCT: Heterogeneity in Ranking Perceptions(Expenses)

	D.V.: Willingness to Donate			
	(1)	(2)	(3)	(4)
HighExpenses	0.670***	0.603***	0.724***	0.719***
	(0.121)	(0.174)	(0.097)	(0.163)
MediumExpenses	0.217*	0.100	0.437***	0.358**
	(0.121)	(0.168)	(0.095)	(0.162)
High Info × *HighExpenses*	0.113			
	(0.185)			
High Info × *MediumExpenses*	0.350*			
	(0.178)			
Quiz Pctl × *HighExpenses*		0.264		
		(0.340)		
Quiz Pctl × *MediumExpenses*		0.633**		
		(0.304)		
Local College			0.060	
			(0.265)	
Local College × *HighExpenses*			0.199	
			(0.322)	
Local College × *MediumExpenses*			-0.547	
			(0.336)	
Home-College Dist.				0.084
				(0.123)
Home-College Dist. × *HighExpenses*				0.010
				(0.143)
Home-College Dist. × *MediumExpenses*				0.045
				(0.148)
College tier Treatment & Interactions	Yes	Yes	Yes	Yes
N	7600	7600	7600	7600
N_Respondent	475	475	475	475
Adj. R-squared	0.609	0.609	0.609	0.609

Note. The outcome variable is the response to fundraising vignettes where patients' college and medical expenses are independently randomized. The reference group is the bottom-tier colleges and low expenses mentioned. The outcome variable takes a value between 0 and 20, and the within-respondent standard deviation is 2.81. *High Info* is defined as 53% of the respondents scoring at or above the median within their assigned quiz question sets on college rankings. *Quiz Pctl* is the respondent's score percentiles from the quiz on college rankings. *Local College* denotes colleges in respondents' current or previous province of residence. Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 14: RCT: Preference Heterogeneity

	Dependent Variable: Willingness to Donate				
	(1)	(2)	(3)	(4)	(5)
TopTier	0.247**	0.495***	0.592***	0.082	0.156
	(0.101)	(0.138)	(0.203)	(0.122)	(0.166)
SecondTier	-0.079	0.007	0.317	-0.108	-0.004
	(0.081)	(0.123)	(0.247)	(0.101)	(0.169)
Graduate × *TopTier*		-0.427**	-0.336		
		(0.172)	(0.222)		
Graduate × *SecondTier*		-0.144	-0.353*		
		(0.162)	(0.210)		
Merit_minded × *TopTier*				0.463**	0.455**
				(0.210)	(0.210)
Merit_minded × *SecondTier*				0.081	0.090
				(0.169)	(0.169)
HighExpenses	0.728***	0.591***	0.594***	0.808***	0.816***
	(0.094)	(0.130)	(0.131)	(0.121)	(0.122)
MediumExpenses	0.401***	0.221*	0.204	0.367***	0.374***
	(0.091)	(0.132)	(0.134)	(0.118)	(0.118)
Graduate × *HighExpenses*		0.242	0.244		
		(0.161)	(0.163)		
Graduate × *MediumExpenses*		0.313*	0.345**		
		(0.173)	(0.175)		
Merit_minded × *HighExpenses*				-0.233	-0.236
				(0.188)	(0.190)
Merit_minded × *MediumExpenses*				0.100	0.090
				(0.183)	(0.183)
Respondent FE, Vignette FE, & Question Sequence FE	Yes	Yes	Yes	Yes	Yes
Col. Prov. FEs & Local College	No	No	Yes	No	Yes
Adj. R-squared	0.64	0.64	0.64	0.64	0.64
Number of Obs.	7,600	7,600	7,600	7,600	7,600

Note. The reference group is the bottom-tier colleges and low expenses mentioned. The outcome variable takes a value between 0 and 20, and the within-respondent standard deviation is 2.81. *Graduate* denotes that the vignette depicts a graduate instead of a current student. *MeritMinded* is a dummy indicating one-third of the respondents who self-reported to be more meritocratic, defined by their subjective weight given to personal qualities/ability, college tier, and education level depicted in the vignettes. Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 15: RCT: Respondent Heterogeneity

	Dependent Variable: Willingness to Donate				
	(1)	(2)	(3)	(4)	(5)
TopTier	0.247**	0.083	0.090	0.428***	0.153
	(0.101)	(0.136)	(0.125)	(0.157)	(0.173)
SecondTier	-0.079	-0.144	-0.104	0.010	-0.084
	(0.081)	(0.114)	(0.107)	(0.123)	(0.147)
RES_GoodCol × *TopTier*		0.326			
		(0.200)			
RES_GoodCol × *SecondTier*		0.132			
		(0.162)			
RES_Male × *TopTier*			0.371*		
			(0.206)		
RES_Male × *SecondTier*			0.052		
			(0.165)		
RES_Young × *TopTier*				-0.334*	
				(0.201)	
RES_Young × *SecondTier*				-0.168	
				(0.165)	
RES_HighIncome× *TopTier*					0.234
					(0.226)
RES_HighIncome × *SecondTier*					0.110
					(0.186)
Respondent FE, Vignette FE, & Question Sequence FE	Yes	Yes	Yes	Yes	Yes
Expenses Treatment & Interactions	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.64	0.64	0.64	0.64	0.63
Number of Obs.	7,600	7,600	7,600	7,600	6,192

Note. The reference group is the bottom-tier colleges and low expenses mentioned. The outcome variable takes a value between 0 and 20, and the within-respondent standard deviation is 2.81. *RES_GoodCol* indicates that the respondent self-reported attending a college ranked 200 or above. *RES_Young* indicates if the respondent's age is under 30. *RES_HighIncome* indicates if the respondent's self-reported salary is above CNY 7500. Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 16: RCT: Respondent Heterogeneity(Expenses)

	Dependent Variable: Willingness to Donate				
	(1)	(2)	(3)	(4)	(5)
HighExpenses	0.728***	0.747***	0.869***	0.594***	0.750***
	(0.094)	(0.127)	(0.121)	(0.132)	(0.146)
MediumExpenses	0.401***	0.425***	0.434***	0.402***	0.344**
	(0.091)	(0.128)	(0.125)	(0.130)	(0.163)
RES_GoodCol × *HighExpenses*		-0.043			
		(0.188)			
RES_GoodCol × *MediumExpenses*		-0.052			
		(0.181)			
RES_Male × *HighExpenses*			-0.326*		
			(0.191)		
RES_Male × *MediumExpenses*			-0.070		
			(0.180)		
RES_Young × *HighExpenses*				0.249	
				(0.186)	
RES_Young × *MediumExpenses*				-0.007	
				(0.181)	
RES_HighIncome × *HighExpenses*					-0.069
					(0.203)
RES_HighIncome × *MediumExpenses*					0.009
					(0.208)
Respondent FE, Vignette FE, & Question Sequence FE	Yes	Yes	Yes	Yes	Yes
College Tier Treatment & Interactions	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.64	0.64	0.64	0.64	0.63
Number of Obs.	7,600	7,600	7,600	7,600	6,192

Note. The reference group is the bottom-tier colleges and low expenses mentioned. The outcome variable takes a value between 0 and 20, and the within-respondent standard deviation is 2.81. *RES_GoodCol* indicates that the respondent self-reported attending a college ranked 200 or above. *RES_Young* indicates if the respondent's age is under 30. *RES_HighIncome* indicates if the respondent's self-reported salary is above CNY 7500. Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table 17: RCT: Knowledge of college ranking

	Total deviation from actual rank		*No. of correct answers*	
	(1)	(2)	(3)	(4)
Tier A (1-50)	0.191***	0.191***	0.100***	0.101***
	(0.054)	(0.054)	(0.026)	(0.026)
Tier B (51-100)	0.229***	0.229***	0.005	0.006
	(0.047)	(0.047)	(0.025)	(0.025)
Tier C (101-200)	0.006	0.007	-0.119***	-0.118***
	(0.044)	(0.044)	(0.025)	(0.024)
Tier D (201-400)	-0.219***	-0.219***	-0.160***	-0.160***
	(0.039)	(0.039)	(0.021)	(0.021)
Local College	0.141***	0.096**	0.062**	0.035
	(0.045)	(0.047)	(0.029)	(0.029)
Respondent FE	No	Yes	No	Yes
N	4750	4750	4750	4750
N_Respondent	475	475	475	475
Adj. R-squared	0.034	0.147	0.035	0.130

Note. Results from 10 multiple-choice questions on college ranks. Each question has five options. The reference group is the lowest-ranked college (ranked below 400). Standard errors clustered at the respondent level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

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Appendix A Observational Data

A.1 Information Extraction using GPT

Workflow

- Pose clear questions and provide detailed instructions when designing the prompt
- Specify the desired output format
  e.g. Ask for delimiters between answers in the output for easy parsing
- Run on a subset of data with a size of 30-60 observations, get responses from API
- Manually create the validating data (the right answer)
- Extract key strings from API responses by regular expression, which is used for generating variable (ChatGPT is good at crafting regular expressions.)
- Evaluate the response in terms of accuracy and ease of parsing, refine the prompt iteratively
- Compare different models or versions for performance and cost-efficiency
  e.g. GPT4 vs GPT3.5, or truncate long input vs. using longform-compatible model
  Generally, versions with more model parameters deliver superior results but can also be slower and costlier.
- Evaluate the impact of inference parameters
  1. *Temperature* (randomness across responses) setting to 0 is usually preferred unless you are "averaging" responses from several trials.
  2. modify the model's likelihood to talk about new topics or repeat old if necessary
- Generating variables from extracted strings
- It may also be useful to produce a quality measure for the variables before:
  1. flagging anomalies to be manually reviewed
  2. defining missing value

Remark

- Multiple questions (or instructions) can be posed in one prompt, but the responses to each would be affected by the others. Asking more than ten questions may compromise the response quality.
- When the target information is complex, it would be better to break the task into several steps, asking multiple questions sequentially. [34]
- Fine-tuning the GPT model became available on Aug 22, 2023, providing the researchers another option in completing information-extracting tasks. It might help reduce cost by shortening the prompt, as the model internalizes your goal and metrics.

Example

Prompt:

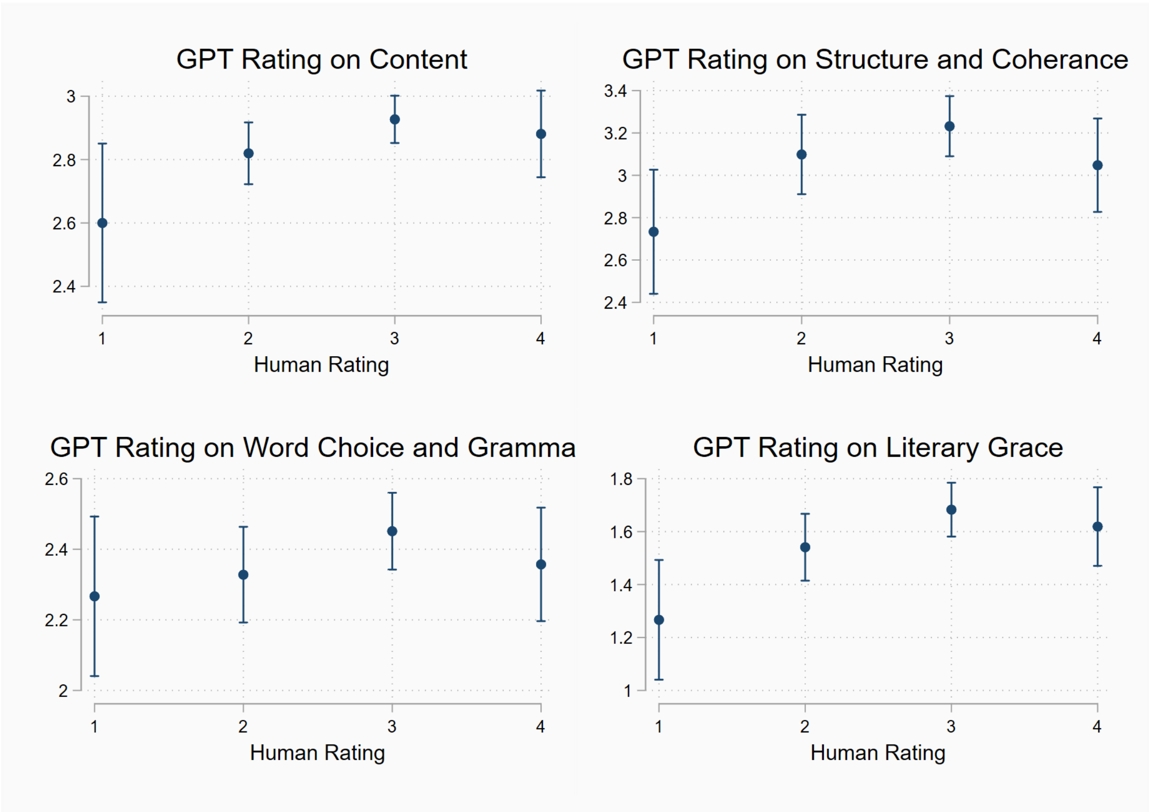
Extract the following information based on the title and content of the article. Print one answer each line. Do not repeat the questions. If unsure, you can answer "not mentioned". [List of questions here]
Title: [Title of the story here]
Content: [Content of the story here]

Sample parsed Response :

[34]This is similar in spirit to the magic keyword of "step-by-step" in prompt design.

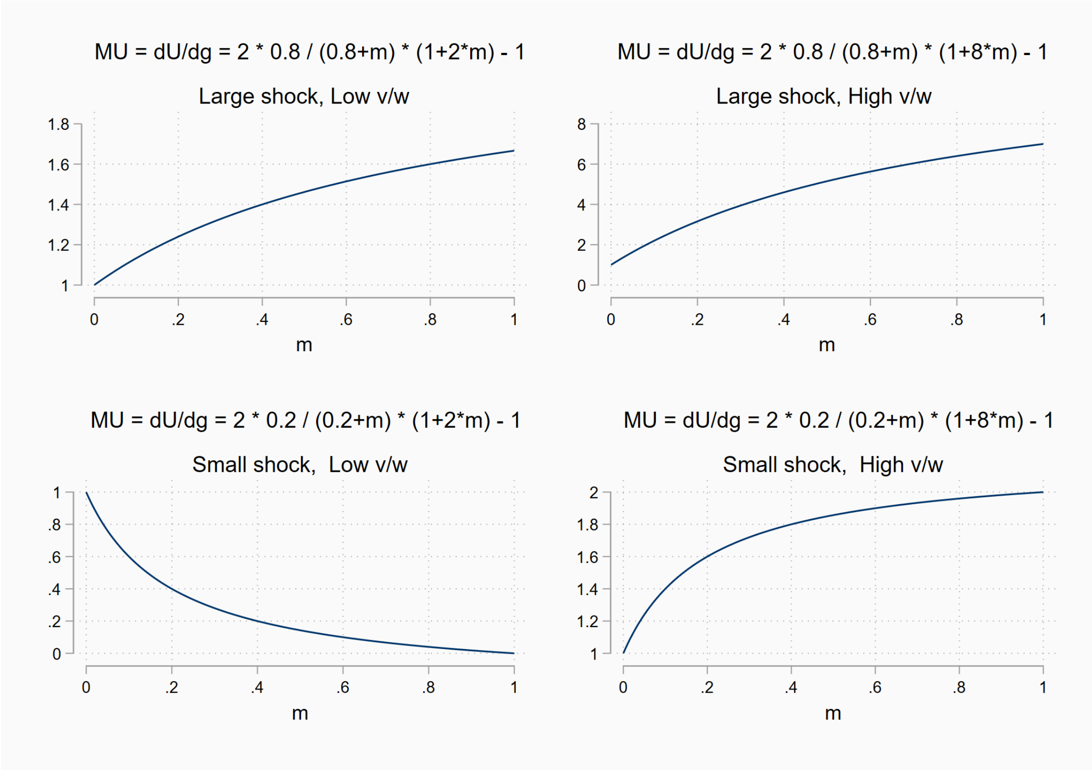
1. The patient has severe cranial trauma, brain hematoma, and contusion, and is in critical condition. (Q1: What illness does the patient have?)
2. The patient's family comes from Tianjiaweicun, Liangjiadian Town, Yutian County, Tangshan, Hebei. (Q2: From which province and city does the patient's family come?)
3. At least 60,000 yuan is required for emergency expenses and 30 days of ICU treatment, as well as subsequent high rehabilitation treatment costs. (Q3: How much is needed in total for medical treatment?)
4. The patient is the narrator's younger brother. (Q4: What relation is the patient to the narrator?)
5. The patient is 26 years old.
6. The patient's gender is male.
7. The patient is pursuing a master's degree at Xi'an University of Technology.
8. The narrator's age is not mentioned.
9. The narrator's gender is female.
10. It is not mentioned in the text which college the narrator attended.
11. It is not mentioned whether the person attending college has graduated.
12. It is not mentioned which year the person attending college is in.
13. The patient's family comes from Tianjiaweicun, Liangjiadian Town, Yutian County, Tangshan, Hebei.

Figure A1: Validation of GPT's rating on writing quality



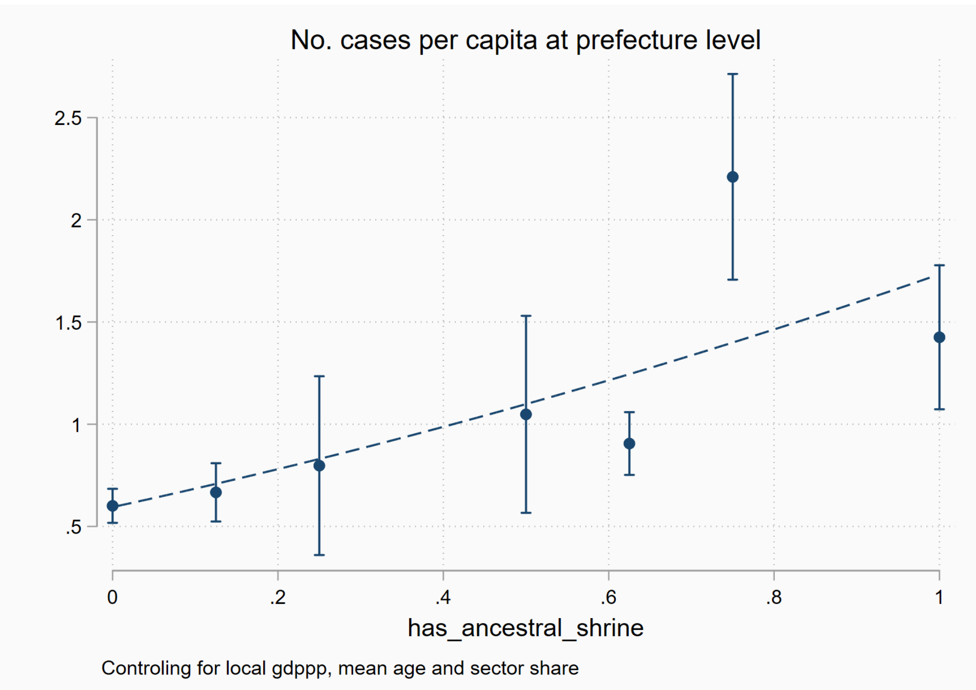
Note: The sample includes 200 campaigns randomly drawn from the main sample. *Human Rating* is a single overall rating on the writing quality of the story, rated by a research assistant.

Figure A2: Numerical Example of Donor's Marginal Utility



Note. $U = w - g + 2 \cdot \frac{s}{s+m}(1+vm)\ln(g+1)$, $s \in \{0.2, 0.8\}$, $v \in \{2, 8\}$, marginal utility evaluated at $g = 0$. g denotes the amount of donation, $w - g$ denotes the consumption, s denotes the size of the shock, v denotes the importance of merit in perceived recipients' worthiness relative to that in perceived recipients' wealth, and m denotes recipients' merit.

Figure A3: Medical Crowdfunding Penetration by Local Clan Culture



Note: Binscatter plot with no controls. Dash lines denote a cubic polynomial fit. Samples include all 110,000 campaigns with the recipient's home province identified. The density of ancestral shrines is from *China Family Panel Studies*. *Qschou* has a higher penetration in prefectures where clan culture is stronger, especially in Guangdong, Guangxi, and Fujian.

Table A1: Measure of Tie Strength(Within-donor)

	(1)	(2)	(3)	(4)	(5)
	Dona.Seq.	DonorCommented	Multi Dona.	Mention Ties	$Ncamp_i$
Rank	185.9***	-0.0044***	-0.00096***	-0.0012***	0.0087***
	(2.62)	(0.00022)	(0.00016)	(0.00011)	(0.0012)
Donor FE	✓	✓	✓	✓	✓
Adj. R-squared	0.10	0.11	0.014	0.047	0.29
Number of Obs.	664,218	664,218	664,218	664,218	664,218

Note. Dona.Seq. stands for the ordinal sequence of donation, a larger number means a later donation. *Multi Dona.* indicates the repeat donor donated more than once to the same campaign *Mention Ties* indicates that the comment (or its reply) to the donation contains words indicating strong social ties (e.g. friend). $Ncamp_i$ the observable ordinal donation sequence on the donors' part, a larger number means a later campaign the donor contributes to.

Table A2: Variable List

CONTENT VARIABLE	METHOD	SOURCE
College	string match, manual proofreading	Text
Disease category	HanLP named entity recognition, GPT3.5 Q&A	Page, text
Fundraiser-patient relationship	string match + HanLP coreference resolution,	Text
Patient's hometown province	HanLP named entity recognition, GPT3.5 Q&A	Text
Patient age	Regex, GPT3.5 Q&A	Text
Patient gender	Regex, GPT3.5 Q&A	Text
Medical expenses mentioned	string match, + GPT3.5 Q&A	Text
Graduation/ Employment status	GPT3.5 Q&A	Text
Fundraising target		Page
Total amount raised		Page
LANGUAGE VARIABLE		
Positivity	Xiezuomao writing editor	Text
Emotion intensity	Xiezuomao writing editor	Text
Average word length	HanLP Word Segmentation	Text
Average sentence length	Xiezuomao writing editor	Text
Writing quality	openai-GPT3.5 Q&A	Text
Grammar mistake density	openai-GPT4 Q&A, Xiezuomao editor	Text
Topic coverage	openai-GPT4 Q&A	Text

Note. Disease category includes 37 categories of disease, uncommon diseases and cases with multiple diseases are binned into separate categories. *Graduation/ Employment status* takes three values: current student, soon-to-be or newly-minted. graduates without a job, graduates with a job mentioned. *Positivity* measures positive sentiment of words *Writing quality* is the sum of 4 subscores rated according to rubrics adapted from TOEFL writing. *Topic coverage* is the proportion of words spent on each topic. *Writing quality* is the sum of 4 subscores rated according to rubrics adapted from TOEFL writing. *College* and *fundraiser-patient relationship* are proofread manually to ensure accuracy.

Table A3: Fundraising for Oneself vs. By a Peer (Young Patient Sample)

	Dependent Variable: Donation Amount			
	(1) Full Sample	(2) Repeat donor	(3) Repeat donor	(4) Repeat donor
College Rank (per #100)	0.901***	0.283***	0.260**	0.156
	(0.177)	(0.0841)	(0.121)	(0.120)
For Oneself × College Rank	-0.0588		0.0466	0.228
	(0.253)		(0.141)	(0.147)
Postgraduate	3.361***	0.879*	0.886*	2.246***
	(1.154)	(0.526)	(0.521)	(0.718)
For Oneself × Postgraduate	-1.927			-2.921***
	(1.465)			(0.824)
Expense (CNY 100K)	0.150	0.152**	0.152**	0.167*
	(0.147)	(0.0688)	(0.0687)	(0.0937)
For Oneself × Expense	0.470**			-0.0208
	(0.197)			(0.110)
For Oneself	-2.568*	-0.864**	-0.758	0.103
	(1.559)	(0.354)	(0.535)	(0.870)
Donor FEs	No	Yes	Yes	Yes
Basic Controls	Yes	Yes	Yes	Yes
Content Controls	Yes	Yes	Yes	Yes
Textual Controls	Yes	Yes	Yes	Yes
Adj. R-squared	0.036	0.55	0.55	0.55
Number of Obs.	2,294,122	193,657	193,657	193,657

Note. Sample: Campaigns for young patients with college mentioned. *For Oneself* indicates the patient is fundraising for herself, as opposed to fundraised by another young adult. The median donation amount is CNY 10. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Donations larger than CNY 300 and those with signs of strong ties are excluded. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors clustered at the campaign level *, **, and *** indicate significance at the 10, 5, and 1% levels.

Table A4: Students vs. Graduates

	Dependent Variable: Donation Amount					
	(1) Young	(2) Young	(3) Young	(4) Senior	(5) Senior	(6) Senior
College Rank (per #100)	0.786***	0.343***	0.397***	0.463***	0.261***	0.251***
	(0.186)	(0.103)	(0.107)	(0.106)	(0.0515)	(0.0522)
Graduated × College Rank	0.155	-0.121	-0.217	0.873***	-0.00844	0.0594
	(0.262)	(0.155)	(0.155)	(0.278)	(0.118)	(0.134)
Postgraduate	1.232	0.889*	0.137	3.400***	0.288	0.500
	(1.039)	(0.534)	(0.680)	(0.879)	(0.358)	(0.407)
Graduated × Postgraduate	2.144		1.362	-3.096*		-0.781
	(1.477)		(0.933)	(1.633)		(0.780)
Expense (CNY 100K)	0.381**	0.176**	0.142*	0.434***	0.0656	0.0824
	(0.148)	(0.0722)	(0.0778)	(0.143)	(0.0572)	(0.0607)
Graduated × Expense	0.00945		0.0550	-0.676**		-0.0885
	(0.200)		(0.120)	(0.296)		(0.134)
Graduated	3.694**	0.428	-0.378	13.05***	1.229**	1.764**
	(1.631)	(0.580)	(0.960)	(1.872)	(0.600)	(0.834)
Donor FEs	No	Yes	Yes	No	Yes	Yes
Basic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Content Controls	Yes	Yes	Yes	Yes	Yes	Yes
Textual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.036	0.55	0.55	0.029	0.53	0.53
Number of Obs.	2,227,146	184,636	184,636	1,792,275	137,392	137,392

Note. Sample: Campaigns for young patients with patient's college mentioned or campaigns for senior patients with fundraiser's college mentioned. The median donation amount is CNY 10. Basic controls include disease category, home province, fundraiser-patient relationship, log GDP per capita of the province of the college, and 30 quantiles of donation ordinal position. Content controls include patient demographics, college major, graduation status, and campaigning behaviors. Donations larger than CNY 300 and those with signs of strong ties are excluded. Textual controls include text length, writing quality score, grammar error density, and coverage of content aspects. Standard errors are clustered at the campaign level. *, **, and *** indicate significance at the 10, 5, and 1% levels.

Appendix B Survey Experiment

B.1 Constructing the Vignettes

I construct the vignettes in the following steps:

- Candidate stories are randomly selected from real-world fundraising stories on *Qschou*.
- Excluded stories that are too long, too complicated, not simultaneously compatible with high/ low-ranked colleges, and cases with obvious factual mistakes
- Summarized by ChatGPT to 250-400 Chinese characters (120-200 words)
- Manually proofread the summary to
  1) improve writing coherence,
  2) correct factual mistakes and grammar errors in summarized text
  3) delete repetitive or redundant information
  4) Add back key information, i.e., medical condition, expenses college, job for graduates, if omitted by ChatGPT
  5) Adjust the wording of (expected or realized) expenses
- Exclude or modify the story if realism is compromised after randomization: uncommon major (e.g. veterinary), rare experience (e.g. studying abroad), medical schools
- Anonymization: modify names with homophones without compromising gender salience and delete personal information like address and cell phone number.
- Picked 16 vignettes out of 40 candidates, with the goal of guaranteeing variation in graduation/work status, gender, disease, and other aspects. This allows for heterogeneity analysis and helps keep the respondent attentive
- Replace the university name and amount of expenses by randomization.
- Under the vignette, we ask respondents the following hypothetical question: With CNY 20 in hand, how much do you want to donate to the patient above? (You can keep the rest). The respondents report willingness to donate between CNY 0-20 by scrolling a bar.

B.2 Response Quality Control

Sample Inclusion Restriction Various measures are taken to ensure data reliability. I employed add-on services provided by the platform, including CAPTCHA test and user identity confirmation. I also employed additional sample restrictions: one response allowed per IP address, one response allowed within 10km, filtering out respondents with low platform credit scores.

Attention Checks We designed two attention checks. The first attention check is disguised as the ninth question of the survey. I embedded a one-sentence instruction in the middle of the vignette, asking respondents to choose a specific donation amount. If a respondent skims the text hastily, this embedded instruction would likely go unnoticed. In the second attention check, I asked respondents about the age group of the patients they were shown after the respondents finished reading all 16 vignettes. Any responses that failed any one of the checks would be discarded.

Invalid Respondents Despite passing attention checks, some responses exhibit suspicious patterns like abnormal response similarity. This indicates the presence of "bots" that submit responses generated or assisted by computer programs and "farmers" who deploy server farms to circumvent the platform's location restrictions and respond in bulk (Chmielewski & Kucker 2020). [35]

Such validity concerns have become more pronounced on crowdsourcing platforms after 2018. Researchers have evaluated response reliability on MTurk in recent years (Rouse 2015, Michael & Kucker 2020).

Screening To address the validity issue, I screened the 950 received questionnaires for fraudulent responses by the following procedure. I reviewed any sets of questionnaires emerging from the same city within 5 minutes. A suspicious response would be discarded if three of the four following criteria were met.

1. respondent located within proximity (1km) of the same area
2. Multiple questionnaires with Near-identical distributions of the intended donation. e.g. identical mode, minimum, and maximum
3. Multiple questionnaires with similar self-reported demographics, usually claiming to be highly educated and have a high income, as these samples are rarer on the platform, and the surveyor would be less likely to reject these responses.
4. Similarity in wording or nonsensical answer when reporting the top aspects affecting the donation decisions

   e.g. A: "They are young. The medical condition matters" B: "They are *still* young. The medical condition matters"

   e.g. "Natural Disaster Relief matters to me"

Additional Exclusion Criteria I exclude questionnaires that failed any one of two additional criteria: 1) responses from individuals who spent less than 5 minutes or more than 30 minutes on the survey, as completing the survey too fast or too slow, indicate low quality (Woods et al. 2017) 2) responses with almost no variation in reporting willingness to donate (Namely, reporting the same donation amount for all vignettes but one or two).

Out of 950 initial questionnaires received, 29% failed validity screening, 17% failed attention checks, and 4% responses failed additional exclusion criteria, leaving us a sample size of 475 respondents for wave 1.

[35] Interestingly, some of the text filled in the survey question by identified bot accounts exhibit a style of generative AI like ChatGPT. A data scientist from Credamo acknowledges a small number of users work in teams to make money by completing paid surveys.