Long-Term Effect of Childhood Pandemic Experience on Medical Major Choice: Evidence from the 2003 SARS Outbreak in China

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Abstract:

This study examines the long-term effect of a pandemic on a crucial human capital decision, namely college major choice. Using China's 2008–2016 major-level National College Entrance Examination (Gaokao) entry grades, we find that the 2003 SARS had a substantial deterrent effect on the choice of majoring in medicine among high school graduates who experienced the pandemic in their childhood. In provinces with larger intensities of SARS impact, medical majors become less popular as the average Gaokao grades of enrolled students decline. Further evidence from a nationally representative survey shows that the intensity of the SARS impact significantly decreases children's aspirations to pursue medical occupations, but does not affect their parents' expectations for their children to enter the medical profession. Our discussions on the effect mechanism suggest that the adverse influence of SARS on the popularity of medical majors likely originates from students' childhood experiences.

Keywords: Childhood Experience, College Major Choice, Medical Majors, Pandemic, SARS

JEL Classification: D81, D91, G40, I100, I23, J24

1. Introduction

Pandemics such as COVID-19 or severe acute respiratory syndrome (SARS) create medical crises (Susskind and Vines, 2020), and expose the occupational risk of healthcare workers (HCWs), who are more vulnerable to pandemic-related infections than the general population. During the ongoing COVID-19 outbreak, HCWs were reported around ten times more likely to be infected with the coronavirus (Alberta Health Services, 2020), and "risked their own health to serve their patients" (Hahn, 2020). According World Health Organization (WHO) statistics, one in every ten HCWs was infected with the coronavirus in some countries (World Economic Forum, 2020). Barrett et al. (2020) found that the COVID-19 infection rate among HCWs was 7.3%, compared to 0.4% for non-healthcare workers.[1] Meanwhile, massive media coverage has contributed to the public's awareness of the occupational risk of HCWs during the pandemic. For instance, according to the media reports, 9% of those infected with COVID-19 in Italy were HCWs, and one in four doctors in the UK was on sick leave in March 2020 (International Council of Nurses, 2020; ITV News, 2020). Thus, the public perception of medical occupational risk could increase after a pandemic such as COVID-19, which in turn could cause a long-term "scarring of beliefs" effect on individuals' choices of medical careers, especially when people are concerned about the reoccurrence of an extreme shock such as a pandemic in the future (Kozlowski et al., 2020).

From a developmental perspective, childhood pandemic experience has great potential to shape long-term career choices. In this study, we seek to explore the possible influences of a pandemic-related childhood experience on one important human capital investment decision: high school graduates' choice of medical majors in China. Although prior literature identifies many motives related to childhood environments that

[1] HCWs on the frontline during the battle against SARS also faced high risk and stress, see e.g. Koh et al. (2005).

influence students' college major choice and the enduring effects of adverse events in one's childhood on their education decision, we still have no knowledge of the effect of a medical crisis caused by a pandemic on the choice of medical majors, and ultimately on the future HCWs' labor supply. Research shows that individuals start to form abstract and objective schemas about occupations (Goldstein & Oldham, 1979) in their primary school stage, and these schemas have predictive value for their future occupational choices (Trice, 1991; Trice & McClellan, 1993). It follows that experiencing a pandemic during primary school ages or later may heighten students' perceptions of the occupational hazard of HCWs, and produces a lasting deterrent effect on students' choice to major in medicine or healthcare after high school. Since the possible impact of COVID-19 remains to be seen, the 2003 SARS outbreak in China provides an ideal opportunity to empirically analyze the pandemic's long-term impact on the popularity of medical majors among high school graduates, who experienced SARS in their childhood.

China was the epicenter of the SARS outbreak in 2003, recording over 5,000 cases of infection and 300 fatalities nationwide (Ministry of Health, 2003). Due to fighting on the front lines, many doctors and nurses were infected. According to the statistics, HCWs accounted for around 20% of the infection cases in mainland China. SARS's lasting effects on public perception may possibly be the result of the great volume of national and regional media reports during and after the SARS outbreak.[2] The reports not only covered the progression of the pandemic, but also emphasized the altruistic stories of HCWs who placed their personal health at significant risk. In particular, after the containment of the SARS outbreak, the Chinese government awarded some HCWs the honor of National Outstanding Individuals, drawing more public attention to their sacrifice and

[2] According to the statistic of China Core Newspapers Full-text Database (CCND) that covers the major newspapers published in China, there were 11,476 articles on SARS in 2003.

contribution.[3]

By measuring the intensity of SARS impact at the provincial level, we investigate whether and how childhood pandemic experience affects high school graduates' choice to major in the medical field later. Such impact is uncertain and has not been investigated. The indomitable spirit of HCWs, who risk becoming infected themselves when caring for their patients, may stimulate students' aspirations to pursue this honorable career. In contrast, it is also possible that students' perception of occupational medical risk, that is, a high possibility of infection during a pandemic, could dissuade them from choosing a medical profession.

Pandemics potentially influence the choice of college majors based on two streams of literature, while the direction of the impact remains unclear. First, from a social learning perspective (Bandura, 1977), one's occupational knowledge and career choices are largely driven by observing, learning, and modeling significant others from the family, school, community, media, and other sources. These social learning experiences have been found to influence choices of majors and occupations via their impact on individuals' self-efficacy beliefs (i.e., whether one has the confidence to perform the relevant tasks well) and outcome expectations (i.e., whether one can achieve positive results by doing something) associated with specific choices (Lent, Brown, & Hackett, 2002). In support of this view, Choi et al. (2020) found that superstar performers in an industry are followed by a significant rise in the number of students choosing majors in related fields, due to the "salience effect" that they overestimate the potential of an industry. Fricke et al. (2015) reported on a natural experiment that randomly assigned first-year students a research project and found that exposure to a field of study could influence students' choice of major. In addition, Aucejo et al. (2020) showed the negative effects of the COVID-19 pandemic on

[3] According to the announcement of Chinese central government, 108 local hospitals and other organizations as well as 307 individuals and 36 sacrificed HCWs were recognized with nation-wide honor. (http://www.gov.cn/test/2005-06/28/content_10680.htm)

college students' current and expected education outcomes, suggesting that their education-related belief is sensitive to pandemic shocks. On the one hand, memory of HCWs' sacrifice during the SARS outbreak may help individuals to develop a more realistic and accurate view about the potential risks of this occupation, thereby facilitating better person-occupation fit in their future career choices. On the other hand, this experience could also lead to to more negative outcome expectations about pursuing the medical profession and a lower level of self-efficacy in coping with the severe occupational risks, which in turn, could reduce the preferences for medical majors. Second, from a life-span career development perspective (Super, 1990), the occupational knowledge and experience accumulated in earlier stages have long-term effects on career choices and aspirations in later stages. For example, it has been found that the occupational perceptions and schemas formed at primary school stage significantly predict individuals' actual occupational choices in later stages (Trice, 1991; Trice & McClellan, 1993). Given the pervasiveness of the availability heuristic (i.e., the accessibility of information impacts one's judgment and decision-making, Tversky and Kahneman, 1973), the childhood memory of HCWs during SARS may be easily brought to mind and influence one's cost-benefit analysis of choosing medical occupations (Pachur, Ralph, & Florian, 2012; Sunstein, 2006). Consistently, psychologists and economists have found a durable impact of exogenous adverse events or unusual shocks during childhood on future career development (Adda et al., 2011; Alderman et al., 2006; Almond, 2006; Bernile et al., 2017; Conzo and Salustri, 2019; Meng and Qian, 2009), as well as a significant impact of childhood experiences on risk preference and decision-making in adulthood (Bernile et al., 2017; Brown and Taylor, 2016; Feng and Johansson, 2018; Marquis and Tilcsik, 2013).[4] Accordingly, a childhood pandemic experience has great potential to shape long-term career choices.

[4] We summarize the related literature in Section 2.

We first examine the impact of a pandemic on the popularity of medical majors among high school graduates using the 2003 SARS impact data and the major-level entry grades of the National College Entrance Examination (Gaokao) in China from 2008 to 2016. We show that the impact intensity of the SARS outbreak on students' home provinces significantly dampens their enthusiasm for choosing medical majors, and the negative effect is more pronounced among cohorts who were yet in their primary school stages in 2003. Due to the unavailability of Gaokao data before 2008, a typical pre-treatment trend analysis cannot be performed. We utilize the evidence that the spatial transmission, and therefore the provincial exposure to SARS shock, is random, and exploit the heterogeneous effects among several different sub-groups. We supplement the evidence of causality explanation with two heterogeneous effects: (1) the popularity of traditional Chinese medical majors, which are not affected by SARS (this is because these particular type of medical majors face no exposure to pandemic-related occupation hazards); and (2) the observation that students with higher Gaokao scores tend to shy away from medical majors, resulting in larger effects of SARS on the top colleges. Overall, our findings suggest that the causality explanation of SARS on the diminished popularity of medical majors is highly likely.

Moreover, using representative survey result that recorded parents' expectation of their children's future occupations in China, we documented a negative effect of SARS on children's aspiration to choose a medical profession; however, we find no such influence on the parents or on children who were under school-going age at the SARS outbreak. In addition, we provide evidence that children with higher Chinese literacy test scores tend to be more impacted by SARS. Our findings imply that the adverse impact of SARS on the popularity of medical majors could be the result of students' childhood experiences during a pandemic, such as media exposure and school lockdowns.

Our paper contributes to the rapidly growing Covid-19 literature by identifying a unique long-term effect of a pandemic on medical human capital accumulation. Based on our findings, the public perception of stress on the medical system during a pandemic might cause an unexpected loss of medical talents in the future. While the shortage of medical sources such as masks, ventilators, and other personal protective equipment caused by the pandemic has attracted attention from policymakers and can be replenish in the short term (Ranney et al., 2020), the potential loss of medical talents resulted from the perception of the pandemic is yet to be investigated and can only be addressed with long-term effort.

Our paper also contributes to the literature regarding how pandemic-related childhood experiences affect one's lifelong decisions by providing evidence of the effect of childhood exposure to SARS media reports on one's subsequent aversion to medical major. While there are evidences illustrating the important role of childhood experience in shaping risk preference and decision-making styles in adulthood (Bernile et al., 2017; Feng and Johansson, 2018; Jiang et al., 2016), few examined how childhood experience of pandemic influences the career decisions and choices in later life stages.

Thirdly, our paper extends the literature on risk-return trade-off decisions in human capital investment (Christiansen et al., 2007; Kerr et al., 2020; Koerselman and Uusitalo, 2014) and choice of college majors (Altonji et al., 2015; Hoxby, 2003, 2004; Lemieux, 2014; Stinebrickner and Stinebrickner, 2011; Wiswall and Zafar, 2015), by emphasizing the risk side factors instead of the return side factors underscored in most of the previous literature. Childhood exposure to pandemic experience and related media reports could potentially influence one's evaluation of the occupational risk of HCWs.

The remainder of this paper is organized as follows: Section 2 describes the institutional background and related literature. Section 3 presents our data and variables. Section 4 reports our main findings and Section 5 further discusses the potential mechanism. Section 6 concludes the paper.

2. Institutional background and related literature

2.1 SARS outbreak

In November 2002, a form of atypical pneumonia named SARS was first found in the Guangdong province of China and began spreading rapidly around the world. Over the next several months, 8,096 people in more than 20 countries contracted this new viral illness, leading to over 800 deaths. Global medical practitioners have paid great personal costs to combat SARS, and WHO declared that SARS was finally contained on 5 July 2003.

China was the epicenter of the SARS outbreak and suffered the most from its impact. Having first appeared in Guangdong, SARS quickly spread to Beijing and other provinces in China. Eventually, the outbreak affected 24 provinces in mainland China, causing 5,328 infections and 332 fatalities.[5] As stated earlier, around 20% of the infection cases were HCWs.

Figure 1 illustrates the geographic distribution of SARS's impact in mainland China. Guangdong and Beijing were the two most severely impacted areas, with more than 1,000 infections. Prior researches have studied the provincial distribution of SARS and show that the spread of SARS is mainly "linked to just a small number of so called super-spreading incidents" (Zhong et al., 2003) and that "SARS spread to new epidemic areas randomly through certain index cases" (Fang et al., 2009). Our exogeneity test later also shows that SARS is uncorrelated with many of observed provincial factors (see Table 4). These evidence alleviate our concern that the SARS's impact may be correlated to the provincial level characteristics such as medical service.

Figure 1

2.2 Gaokao examination

The National College Entrance Examination, commonly known as Gaokao, is an examination administered

[5] Source of data: Ministry of Health, https://web.archive.org/web/20030801083745/http://www.moh.gov.cn/zhgl/yqfb/index.htm.

by the Ministry of Education in China annually in June for entrance into almost all higher education institutions at the undergraduate level. It is usually taken by students, the majority of whom are 18 years old, in their last year of senior high school.[6] For some provinces, the Gaokao examination is uniformly designed by the Ministry of Education and students take the exact same examination. However, the Ministry of Education also allows certain provinces to administer provincially customized examinations. For this reason, the distribution of Gaokao grades varies among provinces and from year to year.

After receiving their overall Gaokao grades, students apply for admission to colleges by submitting a list of their majors, ranked in order of preference, to several colleges. Students can only be admitted to a college based on the choice of major that they have applied for. A college usually pre-sets a fixed admission quota for each major in each province, and accepts students strictly according to the applicants' Gaokao grades ranking. Consequently, admission to the top colleges and popular majors are highly competitive in all provinces, and require high Gaokao grades. The Gaokao entry grades of enrolled students therefore represent the popularity of majors and colleges, given that the admission quota for all the college majors remain highly stable over time across the country (Bo et al., 2020).

In China, only college graduates from medical majors are qualified to take the Doctor Qualification Examination,[7] and become licensed doctors after passing it.[8] In other words, students who wish to pursue the medical doctor profession must hold medical college degrees.

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[6] The students are either social-science-oriented or natural-science-oriented during their high school and study different subjects accordingly. In addition to the common mandatory subjects such as standard Chinese and mathematics, social-science students study history, political science, and geography, while those in natural-science study physics, chemistry, and biology.

[7] The majority of Gaokao examination takers are enrolled into vocational academies, which are vocation skill oriented and require lower Gaokao grades than colleges.

[8] See the Requirements for Registration for the Doctor Qualification Examination (2014) jointly issued by the Health and Family Planning Commission, Ministry of Education, and Medicines Administration Agency in China.

2.3 Related literature

This study is directly linked to several strands of literature. First, our study contributes to the vast literature on students' education choice. Hoxby (2003, 2004) and Patnaik et al. (2020) provided a comprehensive review in this field. A number of prior studies evaluated factors related to students' major choices, such as expectations of future earnings and risk preference (Betts, 1996; Fossen and Glocker, 2017; James et al., 1989; Lemieux, 2014; Zafar, 2013), wage differences between majors (Altonji et al., 2012, 2015; Bhattacharya, 2005; James et al., 1989), preparation and innate ability (Arcidiacono, 2004; Ost, 2010; Stinebrickner and Stinebrickner, 2011), gender difference and preference (Dickson, 2010; Goldin, 2014; Wiswall and Zafar, 2015; Zafar, 2013), family income and background (Caner and Okten, 2010; Freeman and Viarengo, 2014; Saks and Shore, 2005), as well as scholarships and financial aid (Avery and Hoxby, 2004).

Second, our work relates to the literature on the demand for medical education, and therefore the labor market supply of HCWs. The high pecuniary returns of medical education observed in the US and other developed countries significantly explain the demand for medical education (Leighton and Speer, 2020; Nicholson, 2008; Quinn and Price, 1998; Sloan, 1971). However, the mean earnings of Chinese HCWs are currently ranked among the lowest in the Chinese economy because the majority of HCWs are employees of public hospitals and their salaries are subject to strict government regulation (Qin et al., 2013). The perception of the high occupational risk of HCWs during the SARS outbreak could drive the expected risk adjusted return of medical education even lower, which is supported by evidence observed in the violence against doctors in China (Bo et al., 2020).

Third, our work adds to the literature on the enduring effect of childhood experiences on risk preference and decision-making in adulthood. As surveyed in Marquis and Tilcsik (2013), beliefs and risk attitudes formed in early life significantly influence individuals' lifelong decision-making processes, e.g., CEOs' early-life exposure to fatal disasters could permanently impact corporate risk-taking (Bernile et al., 2017), the Great Chinese Famine rendered CEOs more risk averse (Feng and Johansson, 2018), parental behavior influences their offspring's saving behavior in adulthood (Brown and Taylor, 2016), rural childhood experiences reduce individuals' stock market participation (Jiang et al., 2016), and growing up in a high crime neighborhood affects future criminal behavior (Damm and Dustmann, 2014). In addition, other works have found an enduring negative effect of various adverse events or unusual shocks in (early) childhood on individuals' later decision making, education attainment, and wellbeing, e.g., the loss of a parent (Adda et al., 2011), extreme drought and civil war (Alderman et al., 2006; Alfano and Görlach, 2019), natural disasters (Bernile et al., 2017), famine (Meng and Qian, 2009), divorce legalization (González and Viitanen, 2017), as well as evidence of certain events affecting cohorts in utero, such as the 1918 influenza pandemic (Almond, 2006).[9]

Lastly, we also join the ongoing discussion on both the short- and long-term economic impacts of a pandemic. A growing volume of studies have explored the impact of the COVID-19 pandemic and mitigation policies, most of which focus on the impacts over a short time horizon (Atkeson, 2020; Auray and Eyquem, 2020; Eichenbaum et al., 2020; Elenev et al., 2020; Ferguson et al., 2020; Kong and Prinz, 2020). Meanwhile, other works have studied the long-term effects of a pandemic. Jorda et al. (2020) found a sustained downward trend of interest rates, even decades after a pandemic, using a dataset of major pandemics since the 14th century. Several papers have documented the long-term effects of the 1918 influenza pandemic: Correia et al. (2020) documented a persistent decline in economic activity after that pandemic and Almond (2006) showed lower

[9] These two streams of works are echoed by a large volume of literature on the long-term effect of childhood exposure, for example, the residential neighborhoods, immigration, and kindergarten, teacher, and parental influences (Adhvaryu et al., 2019; Björklund and Salvanes, 2011; Björklund et. al, 2007; Brown and Taylor, 2016; Carlana et al., 2018; Chetty et al., 2011, 2016; Holmlund and Sund, 2008; Holmlund et. al, 2011; Kling et al., 2005, 2007; Ludwig et al., 2013; Sanbonmatsu et al., 2006).

educational attainment of the cohorts in utero during that pandemic. In terms of the mechanism of these effects, Kozlowski et al. (2020) showed that a potential source of the lasting effect of a pandemic comes from a persistent change in people's perceived probability of an extreme negative shock in the future, suggesting that the long-term economic costs of COVID-19 may be many times higher than the short-term output losses.

3. Data and variables

In this section, we describe the three datasets and the key variables used in this study.

3.1 SARS impact data

The first dataset is the provincial impact of SARS in China, released by the Ministry of Health of China. These data include the overall number of SARS infections (*case*) and fatalities (*death*) in each province. In addition, the data also include the infection cases of medical staff, which we measure by the variable *med_case*.

After the containment of the SARS outbreak in late 2003, the central government bestowed a great honor on the nationally outstanding institutions and individuals who fought the pandemic. In this national commendation, 108 institutions (mostly hospitals) were awarded "National Outstanding Organizations in Fighting SARS," and 307 individuals (mostly HCWs) received the title of "National Outstanding Individuals in Fighting SARS."[10] The geographic distribution of these outstanding institutions and individuals measures the sacrifice of HCWs in each province while fighting SARS. Hence, we adopt the provincial number of outstanding institutions (*outstanding_inst*) and the provincial number of outstanding individuals (*outstanding_ind*) as proxies for the sacrifice of HCWs in each province.

In summary, we adopt the following provincial variables to measure the intensity of SARS's impact in this study: *case*, *death, med_case, outstanding_ind* and *outstanding_inst*. The former two variables measure the

[10] Another 36 individuals who died fighting in the frontline were awarded posthumously.

severity of the SARS outbreak in a province, while the latter three describe the impact of the outbreak that HCWs confronted.

3.2 College major entry grade data

The second dataset is the Gaokao admission data. These data are available from 2008 to 2016, and includes the major-level Gaokao entry grades published by Education and Examination Authorities in each province, jointly led by the Ministry of Education in China and provincial education bureaus.[11] Thus, our sample corresponds to students born between 1990 and 1999, as they are expected to take the Gaokao examination at the age of 18.

We are interested in the provincial average entry grade (AEG) of students admitted into each major offered by colleges in each year. The AEG measures the average Gaokao grade of students admitted to a particular major. Further, we calculate a major's *AEG percentile rank.* First, the raw Gaokao scores are pooled in a year-province-track pool with majors of the Gaokao year, the same province from which students are recruited, and the same track (social-science or natural-science)[12]. Then, each major's *AEG percentile rank* is its percentile calculated within each pool, which reflects the percentage of majors with lower or equal AEG in the respective pool. For example, an *AEG percentile rank* of 75% indicates that this major's AEG is higher than 75% of majors in its year-province-track pool. Thus, the *AEG percentile rank* measure is standardized and comparable, as it maps AEGs of different provinces in different years into a scale of 0 to 1, and a higher *AEG percentile rank* indicates a higher popularity of the major (Bo et al., 2020).

To identify the field of majors, we refer to the "Undergraduate Major Catalogue of Higher Institutions"

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[11] We obtain the aggregated Gaokao admission data from the official website of one of the leading educational service providers in China.

[12] *AEG percentile rank* in each province is calculated separately for students of social-science and natural-science tracks, as the enrollment quotas are independent.

issued by the Ministry of Education in China. This catalogue categorizes all available college majors in several fields and further classifies them using 6-digit codes. Each major is categorized into one of several fields such as medical, art, and economics. For example, the medical field includes majors such as dental, clinical, and nursing. The colleges are also classified based on the variety of their majors: comprehensive, science and engineering, medical colleges, and so on. Our data also includes some college-level information, such as the college type and its provincial location.

We conduct a *t*-test to compare the difference of *AEG percentile rank* in provinces with high and low SARS impacts. Specifically, we simply classify the provinces into two samples by the percentile of SARS cases: top 25% (*case* >=22) sample and the bottom 25% (*case* <= 1) sample. In Table 1, we first take the mean *AEG percentile rank* of medical majors in high and low SARS-impact provinces using the full sample of colleges. Then, we calculate the difference of *AEG percentile rank* between the two samples and calculate the *t*-test. The *t*-statistics of the difference are also reported. The results show that the *AEG percentile rank* of high SARS-impacted provinces is -3.036% lower than in provinces with low SARS-impact and this difference is significant at the 1% level.

Moreover, around 400 colleges in China are so-called “first-tier colleges” that have the privilege of admitting the first batch of students in each province and require high admission entry grades. In the sample of first-tier colleges, the mean *AEG percentile rank* of medical majors in provinces with high SARS-impact is 2.249% lower than in provinces with low SARS-impact, which is also significant at 1%.

Table 1

Figure 2 plots the annual fluctuation of the mean *AEG percentile rank* of medical majors in high and low SARS-impacted provinces. In the period of 2008–2016, the *AEG percentile rank* of medical majors in the low

SARS-impacted provinces was higher. In general, the mean *AEG percentile rank* of medical majors increased over time, suggesting that medical majors are gradually gaining popularity among the younger generations. Meanwhile, we observe a pattern that medical majors' *AEG percentile rank* in provinces with high SARS-impact was lower and remained stable during this period.

Figure 2

3.3 Occupational aspirations data

The third dataset is from China Family Panel Studies (CFPS), a nationally representative survey data conducted by the Institute of Social Science Survey (ISSS) of Peking University.[13] The CFPS consists of four questionnaires (Child, Adult, Family, and Community), which include most questions covered in four U.S. counterpart datasets (HRS, NYLS, CDS, and PSID). This dataset is a nationally representative longitudinal dataset that includes individual-, household-, and community-level data on demographic and socioeconomic characteristics, such as gender, income, marital status, educational attainment, family background, and employment status. It covers 25 of 31 provinces/regions and 95% of the total population in mainland China.[14] For our purpose, we focused on the Child and Adult survey results in the CFPS survey.

The CFPS was first conducted in 2010 and consecutively every two years, in 2012, 2014, and 2016. Our primary data source is the 2010 CFPS survey because only this wave included questions about both children's occupational aspirations and parents' expectations for their children's future occupations. The 2010 CFPS

[13] See Institute of Social Science Survey (2015) and the link, https://en.wikipedia.org/wiki/China_Household_Finance_Survey, for a more detailed introduction of CFPS. The CFPS dataset is widely adopted in studies on household finance in China, see e.g. Gong et al. (2020).

[14] Sampling of CFPS was drawn with implicit stratification using a multistage probability approach. Specifically, six provinces: Hainan, Inner Mongolia, Ningxia, Qinghai, Tibet and Xinjiang, are omitted. Five provinces/regions (Gansu, Guangdong, Henan, Liaoning, and Shanghai) were chosen for initial oversampling (1,600 households in each, for a total of 8,000) to achieve regional comparisons, and another 8,000 households were drawn through weighting from the other provinces/regions to make the overall CFPS sample representative of the country.

survey asked child respondents a question about their occupational aspirations: "Which specific occupation do you want to pursue when you grow up?" In addition, parents were asked a similar question about their expectation for their children's future occupation. The specific wording of the question is: "Which specific occupation do you want the child to pursue when he/she grows up?" These specific data allow us to construct two dummy variables: *child med-occupation aspiration* and *parent med-occupation aspiration*, which identify whether the surveyed child and parent named a medical profession as their answer, respectively. In this study, we select the household sample from the 2010 CFPS that have both parent and child respondents.[15] The detailed definitions of the variables are provided in Appendix Table A1 and their summary statistics are in Appendix Table A2.

4. SARS's impact on students' choice of medical majors

4.1 Empirical strategy

In our study, the popularity of medical majors is measured by their *AEG percentile rank*, determined by the Gaokao scores of the enrolled students. The interested variable, the provincial intensities of SARS outbreak, has two sources of variation: first, provinces were differently impacted and had different numbers of cases and deaths during the movement; second, within the same province, children of different cohorts were exposed differently depending on their ages and primary-school attending status.

We first examine the relationship between the intensity of SARS's impact and the popularity of medical majors using the following specification:[16]

$$Y_{i,j,k,t} = \alpha + \beta \cdot X_k + \gamma \cdot Controls_{i,j,k,t} + \lambda_i + \delta_j + \eta_t + \varepsilon_{i,j,k,t} \tag{1}$$

where $Y_{i,j,k,t}$ represents the *AEG percentile rank* of major i of college j, calculated by the enrolled students

[15] The CFPS survey requires the respondents of the Child Survey to be under 15 years old. The matched sample includes 2,333 children (aged 10 to 15 years old) and 3,632 parents. As the 2010 CFPS survey randomly assigned the question to adults about their expectations on their children's future occupation, there were only 1,009 parents who answered the question.

[16] Our regression model is in line with the classic strategy adopted to address the impact across geographical regions, see for instance, Nunn and Wantchekon (2011), Levine et al. (2017), Pierce and Snyder (2017), and Chen et al. (2020).

in province k in year t. X_k is the measure of SARS intensity in province k. $Controls_{i,j,k,t}$ represents the vector of all control variables, and $\varepsilon_{i,j,k,t}$ is the error term. Moreover, λ_i, δ_j and η_t indicate the controls for major, college, and year fixed effects. Standard errors are clustered at the college level.

Regarding control variables in these three specifications, we include a vector of major-, college- and province-level characteristics that may affect students' major choice. We control for provincial socio-economic parameters such as GDP per capita (*GDPPC_home*), number of licensed doctors per 10,000 residents (*licdoc_home*) and its annual growth rate (*licdoc_growth_home*), and number of medical institutions (*medinst_home*) in the students' home province and its annual growth rate (*medinst_growth_home)*. These variables for the province that the college is in are also controlled (*GDPPC_college, licdoc_college, licdoc_growth_college, medinst_college,* and *medinst_growth_college*). To control for the supply aspect of admission, we control for the number of students a major plans to enroll, *admin_quota*, from student's home province, and the total number of undergraduates to be admitted, *enroll_quota*, in the student's home province. As the social-science and natural-science high school students are enrolled according to different quotas in each province, we include a dummy *ns_student* that indicates whether the students study natural-science subjects. Since most colleges are home-biased in allocating their admission quota plan and normally receive a larger ratio of students coming from their home provinces, we distinguish whether a college is in the student's home province by the dummy *home_college*. Moreover, we also control for the effect of medical disputes in students' home provinces, also known as "patient-doctor disputes", which is a major occupational risk for the medical profession in China (Hesketh et al., 2012; The Lancet, 2010, 2014).[17] The controlled variable is the province-

[17] Some severe medical disputes in China have resulted in injuries and even the murder of medical staff, attracting a lot of public attention. Bo et al. (2020) found that newspaper articles on violence against doctors influence students' decisions to study medicine at college.

year number of newspaper articles on medical legal dispute cases (*med_disputes*), summarized from China Core Newspapers Full-text Database (CCNFD). The descriptions for all variables are shown in Table A1 in the Appendix.

4.2 Main results

Our hypothesis is that students' interest in choosing a medical major is negatively influenced by the intensity of the SARS outbreak in their home provinces. If our hypothesis is true, we expect that the primary parameter of interest, the coefficient β, will be significantly negative for specification (1).

We present the results of specification (1) using various measures of SARS's intensity in Table 2. Columns (1) – (5) show that the coefficients of all measures of SARS's impact on medical major's *AEG percentile rank* are significantly negative. This finding confirms our hypothesis that the increase of provincial SARS intensity significantly reduces the popularity of medical majors. Therefore, we demonstrate that the SARS impact leads to a reduction in the average Gaokao scores of students admitted to medical majors, suggesting a decrease in the quality of enrolled students and a loss of medical talents in SARS-impacted provinces.[18]

Table 2

Furthermore, to examine the result from the perspective of SARS intensity per capita, we modify the major explanatory variable in specification (1) to account for the provincial population. Specifically, the SARS measure of the specification (1) is further normalized by the provincial population in number of residences, i.e. $\frac{X}{Population}$. We present the results in Table 3. The regression result is robust when we switch population measure

[18] To rule out the possible effect of population difference across regions, we also adopt the SARS's intensity per capita as a robustness check. These population-scaled measures are calculated by dividing the absolute SARS's intensity measures by the provincial population size and capture the severity of the SARS outbreak within each province. For instance, the variable case is scaled by the population in each province, and we have case per capita (*case_pc*). The result, presented in Appendix Table A3, shows that our finding persists with the population-scaled measure of SARS's intensity.

from provincial population to number of medical personnel in each province.

Table 3

4.3 SARS exogeneity and heterogeneous analysis

Researchers are concerned that the exogeneity of shocks may fail due to the presence of time-varying unobservable, which are correlated with both outcome variables and shocks (Freyaldenhoven et al., 2019). The most common strategy for coping with this issue in the literature is analyzing the provincial major preference trends before the SARS shock in 2003. However, due to the unavailability of Gaokao data before 2008, we have to rely on the following exogeneity test and sub-group heterogeneous analysis to support our causality analysis.

4.3.1 Shock exogeneity examination

The spatial transmission of pandemics is found to be largely attributable to human mobility, as measured by both long-distance airline travel and short-distance commuting (Pei et al., 2018), which is usually uncorrelated with factors influencing students' major choice, such as earning expectation and family consideration (Patnaik et al., 2020). The spread of SARS, specifically, is found to be mainly "linked to just a small number of so-called super-spreading incidents" (Zhong et al., 2003) and spreading "to new epidemic areas randomly through certain index cases" (Fang et al., 2009). Furthermore, we show that the SARS shock is exogenous, in terms of provincial distribution, by running a regression of SARS shock intensity on provincial factors potentially affecting students' major choice, using the data from 2003. Table 4 shows that the provincial intensity of the SARS impact is not affected by potential factors affecting students' major choices, including the economic and medical facility development.

Table 4

4.3.2 Medical major classification and heterogeneous effects: evidence from traditional Chinese medical majors

For heterogeneous analysis, we exploit one special control group: traditional Chinese medical majors. The set-up of college medical majors in China is unique in that medical majors are classified as two parallel groups, that is, the traditional Chinese medical majors, as well as modern medical majors. The former includes majors such as traditional Chinese medicine, while the latter covers the clinical, nursing, preventive medicine majors, etc. Graduates from both types of medical majors are expected to become doctors affiliated to hospitals and have the same level of income and social status, except that they perform different kinds of medical service to patients. However, only graduates of modern medical majors face similar occupational risks to HCWs during SARS, because graduates of Chinese medical majors are expected to work in the Chinese-medicine departments, which are not responsible for treating infectious disease patients directly. Such a difference between Chinese and modern medical majors provides a unique opportunity for us to exploit one more dimensional difference. We use the following specification to test whether the Chinese medical majors would be affected differently:

$$Y_{i,j,k,t} = \alpha + \beta \cdot X_k \cdot I_{Chinese\_med} + \gamma \cdot Controls_{i,j,k,t} + \lambda_i + \delta_j + \phi_k + \eta_t + \varepsilon_{i,j,k,t} \tag{2}$$

where the dummy $I_{Chinese\_med}$ equals one for traditional Chinese medical majors and zero otherwise, ϕ_k represents the province fixed effect, and other notations are the same as the specification (1).

Table 5 reports the results and shows that the coefficients of the interaction terms Intensity of SARS and $I_{Chinese\_med}$ are positive and statistically significant. This finding suggests that the popularity of traditional Chinese medical majors is less impacted by the SARS shock than the modern medical majors. Thus, such a difference between the traditional Chinese and modern medical majors provides a strong support to the conjecture that the concern of HCWs' occupation risk related to treating pandemic patient seems to be a major factor behind SARS's negative impact.

Table 5

4.3.3 Students' bargaining power and heterogeneous impact: evidence from top and ordinary colleges

Students' Gaokao grades represent their bargaining power when choosing college majors because higher scores allow more choices. For example, generally a student with a 95%-ranked Gaokao score could choose most majors and colleges, while another student with only a 30%-ranked Gaokao score has much less major choice freedom. Therefore, if our main findings were causal, we would expect the negative influence of the SARS shock to be heterogeneous among students with different bargaining powers regarding major choice. Students with higher Gaokao grades would be more likely to choose non-medical majors since they have more choices than those with lower Gaokao grades. In other words, we expect that the medical majors in top colleges are more severely impacted than those in ordinary ones. As introduced earlier, around 400 first-tier colleges are normally considered to be the top colleges in China.

Similarly, we compare the effects of SARS on top and ordinary colleges by replacing the dummy $I_{Chinese\_med}$ in the specification model (2) with I_{1st_tier}, which equals one if the major is offered by a first-tier college and zero otherwise. The regression results in Table 6 document that the coefficients of the interested interaction terms are significantly negative. Thus, the findings confirm our conjecture that SARS harms the popularity of medical majors in the top colleges more than in the ordinary ones.

Table 6

4.4 Robustness tests

4.4.1 Alternative identification

We demonstrate that our main findings hold when adopting an alternative identification for the full sample of all majors. To identify the effect of the SARS outbreak on medical majors, we employ the following alternative specification:

$$Y_{i,j,k,t} = \alpha + \beta \cdot X_k \cdot Medical\_major_i + \gamma \cdot Controls_{i,j,k,t} + \lambda_i + \delta_j + \phi_k + \eta_t + \varepsilon_{i,j,k,t} \quad (3)$$

where $Medical\_major_i$ is a dummy that indicates whether major i is a medical major. Table 7 presents the estimation results and shows that the coefficients of SARS's impact intensities are all negative and highly significant. Thus, the results of this alternative identification suggest that the negative relationship between the popularity of medical majors and SARS's impact remains robust.

Table 7

4.4.2 SARS's impact on other majors: placebo tests

Furthermore, we perform placebo tests to demonstrate the robustness of our findings. To be specific, we document that SARS has no impact on the popularity of other majors, by replacing the dummy variable *medical_major* in specification model (3) with the dummy variable *Interested_major,* which indicates whether a major belongs to a particular field of interest. Specifically, we consider some selected fields, including Agriculture, Art, Economics, History, Management, Philosophy, Pedagogy, and Science.[19]

Table 8 summarizes the coefficients of the interaction terms for the different fields of majors. Consistent with our expectation, the coefficients of almost all interaction terms are insignificant. This finding suggests that SARS does not promote or suppress the popularity of non-medical majors.

Table 8

5. Mechanisms

[19] In addition, we further examine two particular majors: Biological Science and Biological Engineering, which are considered closely related to the medical field. The results are consistent, which are not reported for brevity and available upon request.

Although we have documented the significant negative effect of the SARS outbreak on students' choice of a medical major, the mechanism has not yet been discussed. In this section, we probe the underlying influence channel. More specifically, how did the intensity of SARS's impact decrease the popularity of medical majors among the Gaokao takers? We provide evidence that students' childhood experience of SARS is the underlying channel and their exposure to media reports seems to be the possible mechanism.

5.1 Childhood experience

College major choice is a complicated decision with many crucial factors (Patnaik et al., 2020). Our previous evidence of the decreased popularity of medical majors does not necessarily suggest that students' childhood experience of SARS is the main influence channel, although they surely experienced the outbreak as children. There might be other possible channels that explain the decreased attractiveness of medical majors in regions that suffered more severely from the effects of SARS. For instance, an alternative hypothesis is that the negative impact is caused by parents' increased concern about the occupational risk of medical professionals after the SARS outbreak. In this section, our empirical evidence proves that the childhood experience of SARS is likely the channel explaining the students' reduced interest in medical majors because only children's occupational aspirations are significantly and negatively affected.

To investigate the underlying impact channel, we employ the 2010 CFPS survey data on children's occupational aspirations (and their parents' expectations for their future careers) and examine the impact of SARS on children's (parents') aspirations to (let their children) pursue a medical occupation. For simplicity, hereafter, parent's occupational aspiration refers to a parent's expectation for their child's future career. We define two dummy variables: *child med-occupation aspiration* and *parent med-occupation aspiration*, and estimate the following Logit model,

$$Y\_aspiration_{i,k} = \beta_0 + \beta_1 \cdot X_k + \gamma \cdot Controls_{i,k} + \varepsilon_{i,k} \qquad (4)$$

where $Y\_aspiration_{i,k}$ is the dummy equal to 1 if the child (parent) i of province k wishes to choose a medical field as his/her (his/her child's) future career. X_k is the measure of SARS intensity in province k, $Controls_{i,k}$ is a vector of child-, parent- and province-level variables including Children's genders and ages, and the parents' genders, ages, education, and household income. Moreover, we include variables representing the levels of economic and medical development in the respondents' provinces, such as GDP per capita, number of medical institutions, and licensed doctors per 10 thousand residents. Standard errors are clustered at the province level.[20]

5.1.1 Impact on parents' occupational aspiration

We first examine the relationship between the intensity of provincial SARS impact and *parent med-occupation aspiration,* Table 9 reports the estimation results. It shows that the intensity of SARS's impact, measured by different variables, does not have a significant effect on parents' expectations of their children's choice of a medical major. This result suggests that adults' attitudes toward the medical profession are hardly affected by the pandemic experience.

Table 9

5.1.2 Impact on children's occupational aspiration

We replace the parents' expectation with their children's medical occupation aspirational dummy variable, *child med-occupation aspiration*. We consider the children's cohorts and divide the children into two subsamples by age at the time of SARS: pre-school-age cohorts and post-school-age cohorts. Based on whether the cohorts were older reach the school-going age (7-year-olds)[21], we classify the cohorts into two subsamples:

1. Post-school-age cohorts: students older than the primary school-going age in 2003;

[20] The detailed definitions of the variables and summary statistics are provided in Appendix Table A1 and Table A2, respectively.

[21] The typical primary school-going age in China is 7-years-old at the date of September 1st in the year of entrance. Students are expected to participate in Gaokao at 18-years-old after 12 years of education (6 years in primary school and 6 years in high school).

2. Pre-school-age cohorts: students younger than the primary school-going age in 2003.

Because the survey was conducted in 2010 and the surveyed children were aged 10 to 15 years, the pre-school-age cohorts are the group aged 10 to 13 years (3 to 6 years old in 2003) and the post-school-age cohorts are the group aged 14 to 15 years (7 to 8 years in 2003).

We run the model (4) using these two subsamples and report the results in Table 10. Columns (1) – (5) report the regression results of subsample 1 and Columns (6) – (10) report those of subsample 2. The coefficients of SARS's intensity in the regression of subsample 1 are not significant. By contrast, the coefficients of subsample 2 are significantly negative. This contrast shows that the impact of SARS is more evident in the group of post-school-age cohorts. Our finding is consistent with previous literature that studied the negative effect of exogenous shocks in childhood (Chetty et al., 2016) and our previous results of specification (2).

Table 10

To sum up, we find that children's occupational aspirations are impacted by SARS, whereas their parents' expectations are not significantly affected. Our results provide strong evidence that the childhood experience is likely to be the channel explaining the impact of SARS on decreasing the popularity of medical majors. Childhood experiences or memories of the SARS outbreak possibly remind students of the risks of medical occupations when they make their college major decisions. The source of this lasting effect possibly stems from a persistent change in children's perceived probability of the occurrence of a pandemic in the future, in line with the mechanism discussed in Kozlowski et al. (2020). Meanwhile, this negative effect is more pronounced for the group of children over primary-school-going age, who are old enough to retain memories of the SARS experience. In Section 5.2, we further show that this may be explained by the primary-school age children's Chinese literacy and more exposure to television or newspaper reports during the SARS outbreak.

5.2 Media report and students' Chinese literacy level difference

In this section, we further explore exposure to media as the underlying mechanism of SARS's impact on children's aspiration to pursue medical professions. More specifically, we seek to determine how the post-school-age cohorts were more impacted by SARS than the younger pre-school-age cohorts. We provide the evidence of media exposure by documenting that the provincial number of SARS-related newspaper articles has a significant negative effect on the post-school-age cohorts' *child med-occupation aspiration*.

We construct the variable *SARS_news* by obtaining the number of SARS-related newspaper articles of each province in 2003 from CCNFD. In a province, *SARS_news* equals to the number of SARS-related articles appeared in both the national newspapers and the provincial newspapers. First, we rerun model (4) by replacing X_k, the measure of SARS intensity in province k, by the provincial variable *SARS_news*.[22] The results for the samples of pre- and post-school-age cohorts are reported in the Column (1) of Panels A and B in Table 11. Similarly, we document a negative effect of *SARS_news* in the post-school-age cohorts sample, but find no significant result in the younger pre-school-age cohorts sample. One possible explanation for such different impacts on pre- and post-school-age children is their Chinese literacy level difference. Because the primary school students have formally started learning to recognize Chinese characters since their 1st grade, one major difference between the pre- and post-school-age cohorts is the Chinese literacy levels, that is, the ability to read Chinese. Since media coverages about SARS were overwhelming during the outbreak in 2003, it is highly possible that post-school-age cohorts were more exposed to the media report as they had more literary capacity.

Second, we further investigate the moderating effect of children's Chinese literacy levels. The CFPS 2010

[22] We also replace the provincial measure of SARS impact in model (1) by *SARS_news*. The coefficient remains significantly negative, however, is not reported for brevity.

survey asked the grade of children's latest Chinese language subject examination, *Chin_grade*, which we adopt as an approximate measurement of their Chinese literacy levels at the time of the SARS outbreak. Specifically, we explore whether children's Chinese literacy levels may intensify the impact of SARS by estimating the following equation for both pre- and post-school-age samples,

$$Y_{i,k} = \beta_0 + \beta_1 \cdot X_k + \beta_2 \cdot X_k \cdot Chin\_grade_i + \beta_3 \cdot Chin\_grade_i + \gamma \cdot Controls_{i,k} + \varepsilon_{i,k} \quad (5)$$

where X_k represents the measurements of SARS impact and *SARS_news* in province k . Here, we rely on the intuitive conjecture that the volume of medical reports in a province is proportional to its SARS severity, since we do not have media report measure.

We report the regression results in Columns (2) – (7) of Panels A and B in Table 11. Panel A indicates that the aspirations of the pre-school-age cohorts with high Chinese literacy are decreased, though not all coefficients of the interaction terms between *Chin_grade* and X_k are statistically significant. The interaction term with SARS impact variables related to the risk or honor of HCWs, *med_case*, *outstanding_ind* and *outstanding_inst*, are all significant. In particular, Column (7) shows that pre-school-age children with higher Chinese language subject grades are more impacted by the newspaper reports of SARS, *SARS_news.* One explanation is that the pre-school-age cohorts who exhibit higher Chinese language grades later in their primary school were likely to be literate and read before primary school (e.g., taught by family), and thus had a deeper impression of reports on medical professions during the SARS outbreak. By contrast, Panel B show that the interaction terms in the specifications for post-school-age cohorts' aspiration to pursue medical professions are not significant. This finding suggests that Chinese literacy levels cause a unanimous effect on the post-school-age cohorts who had become literate by primary school education at the onset of the SARS outbreak.

Table 11

In sum, our results suggest that childhood media exposure during the SARS outbreak is a possible mechanism through which the epidemic had a lasting effect. Post-school-age children's obtained literacy and pre-school-age children's pre-mature ability to read could have contributed to their exposure to media reports, which in turn left them stronger impressions of SARS. It is noteworthy that we do not claim that media exposure is the only channel through which SARS negatively influenced children's aspirations to become medical professionals. Many other possible channels are worth investigation with proper identifications and measures. For instance, children's memory of their school experiences during SARS such as the school lockdown, could lead to the lasting effect on them.

6. Conclusion

This study examines the long-term effect of epidemics/pandemics on the choice of college majors (medical professions). Using provincial data on the intensity of the SARS outbreak, we find that SARS's impact in students' hometowns discourage high school graduates from choosing medical majors. Further evidence from the CFPS survey data shows that the SARS impact reduced the interest of those children who were over school-going age in 2003 in pursuing medical majors. Coupled with the finding that parents' expectations of their children's future careers remain unaffected by the SARS impact, these findings suggest that the decreased popularity of medical majors after the outbreak very likely originates from students' childhood experiences.

In summary, our study is the first to examine the long-term impact of an epidemic/pandemic on the students' choice of college majors, specifically, medical majors. We contribute to the literature on both individual's education choice and the long-term effect of childhood experiences within the context of disease outbreaks. On the one hand, our findings have the practical implication for labor economics that a pandemic is one additional influencing factor that affects an individual's education choice. On the other hand, our work expands the understanding of the long-term impact of pandemic and documents the lasting influence of pandemic experiences in childhood on human capital investment decisions.

Our findings suggest that children's belief or preference including occupational aspirations are impacted by SARS, but not their parents' expectations, which implies that the current pandemic could also influence children in a very different way from adults. Policymakers should consider both the short- and long-term impacts of pandemic mitigation approaches, targeting differently at children vs. adults, as the provision of information about pandemic could influence children's risk perception differently from their parents.

On the one hand, mass media has the potential to influence the attitudes and behavior of a large community and thus contribute to controlling the evolution of epidemics. Some epidemiology studies on evaluating the media impact on the control of infectious diseases find that media coverage can significantly reduce the severity of epidemic outbreak (see e.g. Lu et. al 2017; Sun et. al 2011; Xiao et. al 2015), and engagement of media of authority increase the compliance of health behavior (Ananyev et al., 2021; Wu & Shen, 2021). Our findings also suggest that it is very likely that media reports about the harsh working conditions of HCWs could contribute to creating a tense atmosphere among the public, which may be beneficial to the containment of the epidemics/pandemics in the short term.

On the other hand, media propagation of pandemic can cause "infodemic", which could potentially exacerbate children's pandemic experience much more severely than their parents. Our results provide strong evidence that the childhood's direct experience or exposure to media reports of SARS may lead to the decreasing popularity of medical majors. Thus, the short-term compliance behavior is achieved possibly at the cost of long-term loss of talents in medical fields.

Therefore, children and adults are influenced by media information in complex ways. While media is an effective channel for agencies to deliver health behavior information and help combating pandemics, that same information may possibly elicit unnecessary fear and lead to infodemic that exacerbates the pandemic's long-term influence. With existing evidence suggesting that official media lead to more compliance (Ananyev et al., 2021; Wu & Shen, 2021), thus careful government intervention is beneficial in the combat against pandemics. According to the long-term impact recognized by this work, direct experience or exposure to media reports can discourage children to pursue medical professions when they grow up. To avoid the long-term shadow of epidemics/pandemics on human capital accumulation among the medical professions and a loss of medical talent, our results suggest that media reports on the risk and occupational stress of HCWs should be tailored carefully especially when the target audience includes children.

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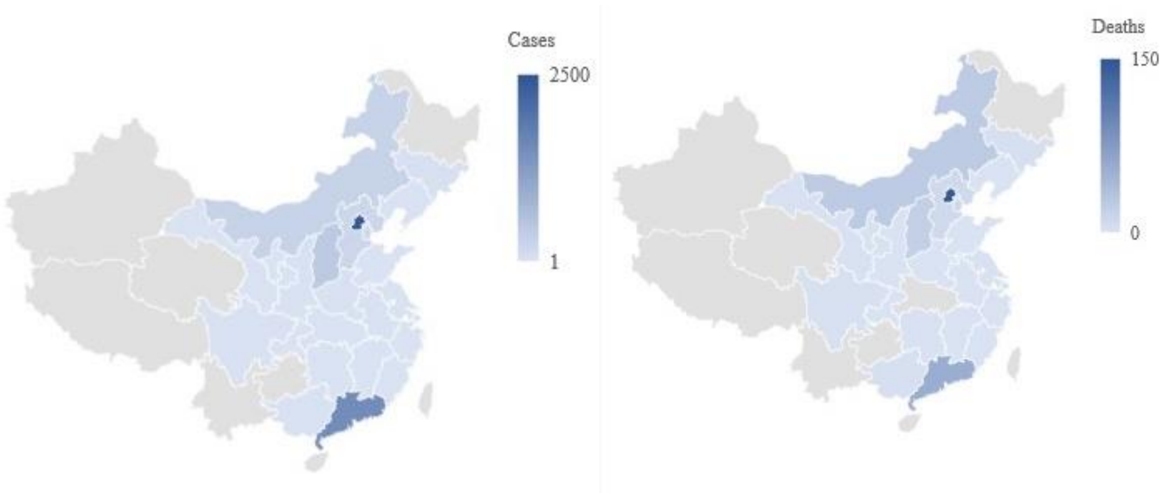
Figures



(a) SARS infection cases

(b) SARS deaths

Figure 1. Geographical distribution of the number of SARS infections and deaths in mainland China

Note: This figure presents the SARS infection and death cases across provinces in mainland China. The darker color represents a greater number of cases in the province.

Source: Ministry of Health of China

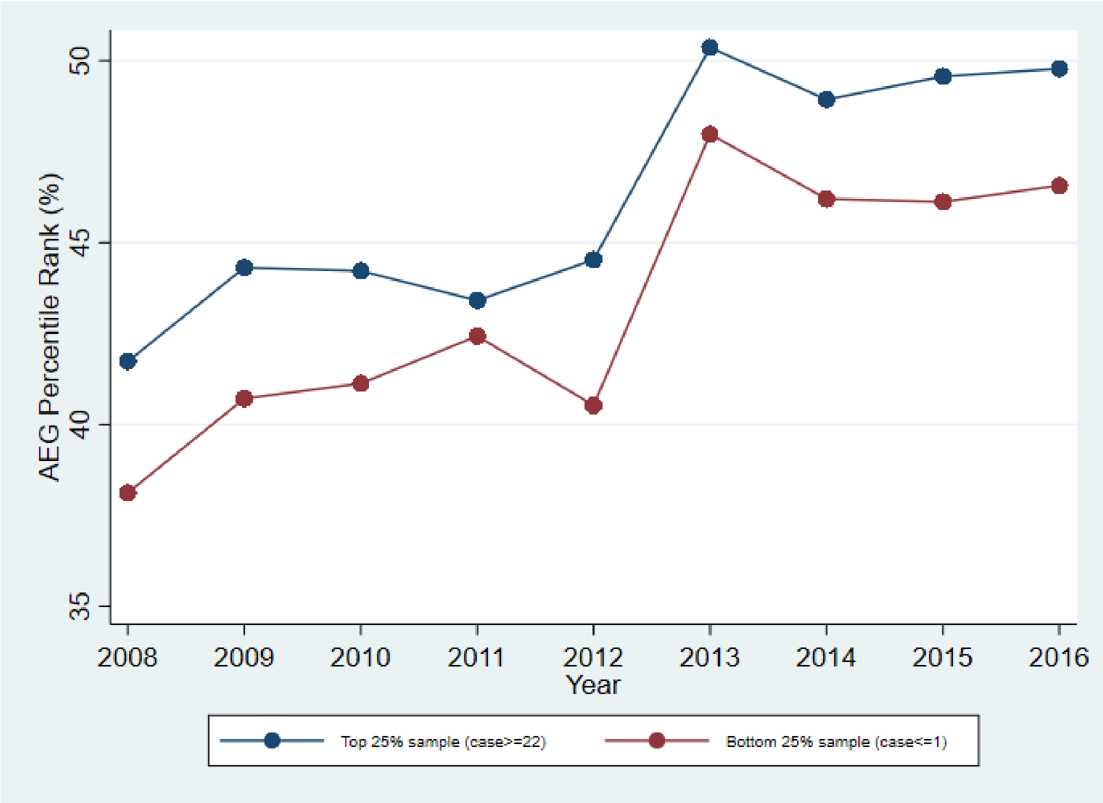


Figure 2. Mean AEG percentile rank of medical majors in high and low SARS-impact provinces

Note: This figure presents the mean AEG percentile rank of medical majors in each province's top 25% sample (*case*>=22) and bottom 25% sample (*case*<=1).

Tables

Table 1: Medical majors' mean AEG percentile rank between provinces with high and low SARS impacts

	Sample 1: High SARS Impact Provinces (*cases* $\geq$ 22)		Sample 2: Low SARS Impact Provinces (*cases* $\leq$ 1)		Sample 1 – Sample 2	
	Means	Observations	Means	Observations	Diff of means	t-value
Full sample	45.608	29172	48.644	28230	-3.036	-13.627
First-tier colleges sample	71.463	3631	74.536	3800	-3.074	-9.500

Note: This table presents the mean *AEG percentile rank* of medical majors in high and low SARS-impacted provinces using the full sample of colleges and in the sample of first-tier colleges. The high SARS-impacted provinces have SARS *cases* $\geq$ 22 and the low SARS-impacted provinces have *cases* $\leq$ 1. The difference of *AEG percentile rank* between the two samples and the t-value are also reported.

Table 2: SARS impact and medical majors' AEG percentile rank

	(1)	(2)	(3)	(4)	(5)
Dependent variable			*AEG Percentile Rank* (%)		
Case	-0.494***				
	(0.085)				
Death		-0.649***			
		(0.140)			
Med_case			-0.456***		
			(0.113)		
Outstanding_ind				-2.358***	
				(0.298)	
Outstanding_inst					-3.260***
					(0.389)
College clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
College FE	YES	YES	YES	YES	YES
Major FE	YES	YES	YES	YES	YES
Observations	76457	76457	76457	76457	76457
R^2	0.797	0.797	0.797	0.798	0.798

Note: This table presents the analysis of the impact of SARS on the popularity of medical majors using the 2008-2016 sample. The dependent variable is college majors' AEG percentile rank. All regressions are controlled for college, major, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Normalized SARS impact and medical majors' AEG percentile rank

	(1)	(2)	(3)	(4)	(5)
Dependent variable	*AEG Percentile Rank* (%)				
Case/Population	-0.432***				
	(0.0728)				
Death/Population		-0.450***			
		(0.108)			
Med_case/ Population			-0.298**		
			(0.0996)		
Outstanding_ind /Population				-2.832***	
				(0.320)	
Outstanding_inst/Population					-2.999***
					(0.411)
College clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
College FE	YES	YES	YES	YES	YES
Major FE	YES	YES	YES	YES	YES
Observations	76457	76457	76457	76457	76457
R^2	0.797	0.797	0.797	0.798	0.798

Note: This table presents the analysis of the impact of SARS on the popularity of medical majors using the 2008-2016 sample. The dependent variable is college majors' AEG percentile rank. All regressions are controlled for college, major, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Endogeneity test of SARS impact proxies

	(1)	(2)	(3)	(4)	(5)
Dependent variables	*Case*	*Med_case*	*Death*	*Outstanding_ind*	*Oustanding_inst*
GDP	-0.081	-0.011	-0.006	-0.000	-0.001
	(0.073)	(0.013)	(0.004)	(0.000)	(0.001)
Income_home	0.036	0.006	0.002	0.000	0.000
	(0.028)	(0.005)	(0.001)	(0.000)	(0.000)
Resident_number	-0.007	-0.001	-0.000	-0.000	-0.000
	(0.014)	(0.003)	(0.001)	(0.000)	(0.000)
Licdoc	0.005	0.000	0.000	0.000	0.000
	(0.016)	(0.003)	(0.001)	(0.000)	(0.000)
Licnur	0.009	0.003	0.000	-0.000	-0.000
	(0.02)	(0.004)	(0.001)	(0.000)	(0.000)
Medinst	-0.012	-0.001	-0.001	-0.000	-0.000
	(0.027)	(0.005)	(0.001)	(0.000)	(0.000)
Urban_rate	1101.000	176.700	72.640	6.836	15.220
	(1236.000)	(225.800)	(66.36)	(5.216)	(14.560)
Dist_to_GD	-0.236	-0.044	-0.013	-0.001	-0.003
	(0.203)	(0.037)	(0.011)	(0.001)	(0.002)
Homecollege_number	7.576	0.557	0.624	0.029	0.145
	(9.785)	(1.788)	(0.525)	(0.041)	(0.115)
Watercoverage	1.506	0.477	-0.012	-0.010	-0.050
	(14.580)	(2.665)	(0.783)	(0.062)	(0.172)
Gascoverage	-2.459	-0.282	-0.113	0.005	0.011
	(12.100)	(2.211)	(0.650)	(0.051)	(0.143)
Observations	31	31	31	31	31
R^2	0.398	0.401	0.431	0.406	0.449

Note: This table presents the results of exogeneity tests of SARS impact, using the provincial data from 2003. The dependent variables are the provincial intensities of SARS impact, SARS *case*, *med_case*, *death*, *outstanding_ind* and *outstanding_inst*. Other variables include provincial characteristics such as *GDP*, income per capita of the province (*avg_income*), number of residents (*resident_number*), total number of licensed doctors (*licdoc*), total number of licensed nurses (*licnur*), number of medical institutions (*medinst*), urbanization rate (*urban_rate*), the distances to Guangdong province (*dist_to_GD*), number of home colleges (*homecollege_number*), coverage rate of water supply (*watercoverage*), and coverage rate of gas supply (*gascoverage*). Standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: SARS impact and medical majors' AEG percentile rank: Effect of Chinese medical majors

	(1)	(2)	(3)	(4)	(5)
Dependent variable	*AEG Percentile Rank (%)*				
$Case \times I_{Chinese\_med}$	0.599***				
	(0.137)				
$Death \times I_{Chinese\_med}$		1.088***			
		(0.216)			
$Med\_case \times I_{Chinese\_med}$			0.783***		
			(0.169)		
$Outstanding\_ind \times I_{Chinese\_med}$				1.778***	
				(0.422)	
$Outstanding\_inst \times I_{Chinese\_med}$					2.902***
					(0.537)
College clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
College FE	YES	YES	YES	YES	YES
Major FE	YES	YES	YES	YES	YES
Observations	76457	76457	76457	76457	76457
R^2	0.810	0.810	0.810	0.810	0.810

Note: This table presents a set of difference-in-difference analyses of the impact of SARS on the popularity of medical majors using the 2008-2016 sample. The dependent variable is medical majors' *AEG percentile rank*, including $I_{Chinese\_med}$ that indicates whether the major is a modern medicine major. All regressions are controlled for province, college, major, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: SARS impact and medical majors' AEG percentile rank: Effect of first tier colleges

	(1)	(2)	(3)	(4)	(5)
Dependent variable			*AEG Percentile Rank (%)*		
$Case \times I_{1st\_tier}$	-0.652**				
	(0.246)				
$Death \times I_{1st\_tier}$		-1.104**			
		(0.417)			
$Med\_case \times I_{1st\_tier}$			-0.678*		
			(0.303)		
$Outstanding\_ind \times I_{1st\_tier}$				-1.918**	
				(0.677)	
$Outstanding\_inst \times I_{1st\_tier}$					-2.298*
					(0.952)
College clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
College FE	YES	YES	YES	YES	YES
Major FE	YES	YES	YES	YES	YES
Observations	76457	76457	76457	76457	76457
R^2	0.811	0.811	0.811	0.811	0.811

Note: This table presents a set of difference-in-difference analyses of the impact of SARS on the popularity of medical majors using the 2008-2016 sample. The dependent variable is medical majors' *AEG percentile rank*, including I_{1st_tier} that indicates whether the major is offered by a first-tier college. All regressions are controlled for province, college, major, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: SARS impact and college majors' AEG percentile rank: Althernative specification

	(1)	(2)	(3)	(4)	(5)
Dependent variable			*AEG percentile rank (%)*		
Case × *Medical_Major*	-0.601***				
	(0.106)				
Death × *Medical_Major*		-0.742***			
		(0.178)			
Med_case × *Medical_Major*			-0.660***		
			(0.131)		
Outstanding_ind × *Medical_Major*				-1.665***	
				(0.328)	
Outstanding_inst × *Medical_Major*					-2.429***
					(0.456)
College clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
College FE	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES
Major FE	YES	YES	YES	YES	YES
N	835245	835245	835245	835245	835245
R2	0.852	0.852	0.852	0.852	0.852

Note: This table presents the analysis of the impact of SARS on the popularity of medical majors. The dependent variable is majors' *AEG percentile rank*. Column (1) - (5) report the regression results of 2008 - 2016 sample. All regressions are controlled for college, major, province, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Effect on SARS's impact on selected other fields of college majors

Dependent variable	*AEG Percentile Rank* (%)							
(Panel A) Interested fields of majors	Agriculture	Art	Economics	History	Management	Philosophy	Pedagogy	Science
Case × *Interested_major*	0.083	-0.035	-0.079	-0.106	-0.006	0.206	0.018	0.009
	(0.107)	(0.617)	(0.054)	(0.142)	(0.037)	(0.181)	(0.140)	(0.051)
College clustered	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
(Panel B) Interested fields of majors	Agriculture	Art	Economics	History	Management	Philosophy	Pedagogy	Science
Death × *Interested_major*	0.206	-0.284	-0.034	-0.244	-0.040	0.312	0.106	0.076
	(0.184)	(0.902)	(0.089)	(0.241)	(0.061)	(0.270)	(0.221)	(0.077)
College clustered	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
(Panel C) Interested fields of majors	Agriculture	Art	Economics	History	Management	Philosophy	Pedagogy	Science
Med_case × *Interested_major*	0.124	-0.128	-0.062	-0.088	-0.023	0.287	0.236	0.077
	(0.148)	(0.633)	(0.063)	(0.174)	(0.045)	(0.216)	(0.168)	(0.058)
College clustered	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
(Panel D) Interested fields of majors	Agriculture	Art	Economics	History	Management	Philosophy	Pedagogy	Science

Outstanding_ind × *Interested_major*	0.819**	-1.028	-0.472*	-0.433	0.141	0.844	-0.047	-0.041
	(0.270)	(2.222)	(0.185)	(0.472)	(0.121)	(0.608)	(0.363)	(0.171)
College clustered	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
(Panel E) Interested fields of majors	Agriculture	Art	Economics	History	Management	Philosophy	Pedagogy	Science
Outstanding_inst × *interested_major*	0.917*	-0.644	-0.352	-0.110	0.257	0.835	0.652	0.173
	(0.436)	(2.450)	(0.236)	(0.569)	(0.151)	(0.656)	(0.487)	(0.188)
College clustered	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the analysis of the impact of SARS on the popularity of some non-medical related majors, using the 2008-2016 sample. The dependent variable is college majors' AEG percentile rank. *Interested_major* is a dummy that equals one if a major belongs to the interested field, and zero otherwise. Columns (1) - (8) of Panels A-E report the coefficient of interaction term of the regressions for the following interested fields: Agriculture, Art, Economics, History, Management, Philosophy , Pedagogy, and Science. All regressions are controlled for college, major, province, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. ∗, ∗∗, and ∗∗∗ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: SARS impact and parent med-occupation aspiration

	(1)	(2)	(3)	(4)	(5)
Dependent variable			*Parent med-occupation aspiration*		
Case	-0.001				
	(0.051)				
Death		-0.082			
		(0.063)			
Med_case			-0.011		
			(0.048)		
Outstanding_ind				0.014	
				(0.251)	
Outstanding_inst					-0.168
					(0.183)
Province clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Observations	1,009	1,009	1,009	1,009	1,009
Pseudo R^2	0.041	0.042	0.041	0.041	0.042

Note: This table presents the results of the analysis of the effect of SARS's impact on *parent med-occupational aspiration*, a dummy indicating whether parents hope their children will pursue medical professions. The measures of SARS intensity are the number of SARS *case*, *med_case*, *death*, *outstanding_ind* and *outstanding_inst* in the respondent's home province. Columns (1) - (5) report the regression results of the surveyed parents. The control variables include *parent_gender*, *medinst_home*, *GDPPC_home*, *urban*, *child_age*, *boy*, *parent_edu*, and *licdoc_home*. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at province level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: SARS impact and child med-occupation aspiration: 10-to-13 years old and 14–to-15 years old cohorts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent variable	*Child med-occupation aspiration*									
Samples	10-to-13 years old (pre-school-age cohorts at SARS)					14-to-15 years old (post-school-age cohorts at SARS)				
Case	0.030					-0.058				
	(0.043)					(0.038)				
Death		0.062					-0.103**			
		(0.062)					(0.047)			
Med_case			0.043					-0.076**		
			(0.041)					(0.032)		
Outstanding_ind				0.063					-0.209	
				(0.217)					(0.177)	
Outstanding_inst					0.105					-0.313***
					(0.161)					(0.115)
Province clustered	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,457	1,457	1,457	1,457	1,457	876	876	876	876	876
R^2	0.049	0.049	0.049	0.048	0.050	0.089	0.090	0.090	0.089	0.089

Note: This table presents the results of the analysis of the effect of SARS impact on *child med-occupational aspiration*, a dummy indicating whether the surveyed child hopes to pursue medical professions. We consider the samples of children aged 10-to-13 years old and 14-to-15 years old, which correspond to the pre- and post-school-age cohort at SARS. The measures of SARS intensity are the number of SARS *case*, *med_case*, *death*, *outstanding_ind* and *outstanding_inst* in the respondent's home province. Columns (1) - (5) report the regression results of 10-to-13 years old's group, while columns (6) - (10) report the regression results of 14-to-15 years old group. The control variables include *household_income*, *medinst_home*, *GDPPC_home*, *urban*, *child_age*, *boy*, *highest_educ*, and *licdoc_home*. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at province level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: SARS impact and child med-occupation aspiration: Effect of Chinese literacy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable				*Child med-occupation aspiration*			
(Panel A) Sample				10-to-13 years old (pre-school-age cohorts at SARS)			
SARS_news	0.198						
	(0.408)						
Case × *Chin_grade*		-0.003					
		(0.002)					
Death × *Chin_grade*			-0.004				
			(0.002)				
Med_case × *Chin_grade*				-0.003*			
				(0.002)			
Outstanding_ind × *Chin_grade*					-0.008*		
					(0.005)		
Outstanding_org × *Chin_grade*						-0.009*	
						(0.005)	
SARS_news × *Chin_grade*							-0.036*
							(0.021)
Province clustered	YES	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES	YES
Observations	1,457	1,358	1,358	1,358	1,358	1,358	1,358
R2	0.051	0.055	0.055	0.055	0.055	0.055	0.055
(Panel B) Sample				14-to-15 years old (post-school-age cohorts at SARS)			
SARS_news	-0.992***						
	(0.348)						
Case × *Chin_grade*		-0.002					
		(0.002)					

Death × *Chin_grade*			-0.001				
			(0.002)				
Med_case × *Chin_grade*				-0.001			
				(0.002)			
Outstanding_ind × *Chin_grade*					-0.008		
					(0.006)		
Outstanding_org × *Chin_grade*						-0.008	
						(0.007)	
SARS_news × *Chin_grade*							-0.016
							(0.018)
Province clustered	YES	YES	YES	YES	YES	YES	YES
Other Controls	YES	YES	YES	YES	YES	YES	YES
Observations	876	776	776	776	776	776	776
R2	0.050	0.050	0.050	0.050	0.050	0.051	0.050

Note: This table presents the results of the analysis of the moderation effect of *Chin_grade* on SARS's impact on *child med-occupational aspiration*, a dummy indicating whether they hope to pursue medical professions. Panel A reports the regression results of 10-to-13 years old sample (pre-school-age cohorts at SARS), while Panel B reports the regression results of 14-to-15 years old sample (post-school-age cohorts at SARS). Column (1) reports the effect of *SARS_news* on *child med-occupational aspiration.* Column (2) - (7) report the regression with the interaction term between *Chin_grade* and the measures of SARS intensity, including the number of *SARS case*, *med_case*, *death*, *outstanding_ind*, *outstanding_inst and SARS_news* in the respondent's home province. The control variables include *household_income*, *medinst_home*, *GDPPC_home*, *urban*, *child_age*, *boy*, *highest_educ*, *licdoc_home*. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at province level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix

Table A1: Variable definitions

Variable Name	Definition	Source
Case	The log number of SARS infected cases in the student's (respondent's) home province, ln(1+ infected cases).	National Health Commission of the People's Republic of China
Med_case	The log number of medical staff SARS infected cases in the student's (respondent's) home province, ln(1+ infected cases).	National Health Commission of the People's Republic of China
Death	The log number of SARS deaths in the student's (respondent's) home province, ln(1+ deaths).	National Health Commission of the People's Republic of China
Outstanding_ind	The log number of individuals awarded "National Outstanding Individuals in Fighting SARS" in the student's home province, ln(1+ individuals).	The State Council of the People's Republic of China
Outstanding_inst	The log number of institutions awarded "National Outstanding Organization in Fighting SARS" in the student's (respondent's) home province, ln(1+ institutions).	The State Council of the People's Republic of China
AEG percentile rank	AEG percentile rank is the percentile of a major's entry score, which reflects the percentage of majors (of the Gaokao year, the same province from which students are recruited, and the same track) with lower or equal AEG.	Authors' calculation
Ns_Student	A dummy variable that equals 1 if the major is a science-related major, and 0 if the student is a liberal art-related major.	Authors' calculation
GDPPC_home	GDP per capita of the student's home province in the Gaokao year in Yuan.	China Statistical Yearbook, National Bureau of Statistics
GDPPC_college	GDP per capita of the college's province in the Gaokao year in Yuan.	China Statistical Yearbook, National Bureau of Statistics

Income_home	Income per capita of the student's home province in the Gaokao year in Yuan.	China Statistical Yearbook, National Bureau of Statistics
Income_college	Income per capita of the college's province in the Gaokao year in Yuan.	China Statistical Yearbook, National Bureau of Statistics
Licdoc_home	Number of licensed doctors per 10,000 residents of the student's home province in the Gaokao year.	China Statistical Yearbook, National Bureau of Statistics
Licdoc_college	Number of licensed doctors per 10,000 residents of the college's province in the Gaokao year.	China Statistical Yearbook, National Bureau of Statistics
Licdoc_growth_home	Annual growth rate of the number of licensed doctors per 10,000 residents of the student's home provinces in the Gaokao year.	Authors' calculation
Licdoc_growth_college	Annual growth rate of the number of licensed doctors per 10,000 residents of the college's provinces in the Gaokao year.	Authors' calculation
Medinst_home	Number of medical institutions of the student's home province in the Gaokao year.	China Statistical Yearbook, National Bureau of Statistics
Medinst_college	Number of medical facilities of the college's province in the Gaokao year.	China Statistical Yearbook, National Bureau of Statistics
Medinst_growth_home	Annual growth rate of the number of medical institutions of the student's home province in the Gaokao year.	Authors' calculation
Medinst_growth_college	Annual growth rate of the number of medical institutions of the college's province in the Gaokao year.	Authors' calculation
Resident_number	The number of residents of the student's home province in the Gaokao year.	China Statistical Yearbook, National Bureau of Statistics

Med_disputes	Number of newspaper articles (in hundred) on medical disputes of the student's home province in the Gaokao year.	China Core Newspapers Full-text Database
Home_college	A dummy variable that equals one if the college is located in the student's home province, and zero otherwise.	Authors' calculation
Admin_quota	Number of students a major plans to enroll from the target province in the Gaokao year.	China Education Online
Enroll_quota	The number of students that enrolled into all colleges in the student's home province.	China Education Online
Medical_major	A dummy variable that equals one if the major is categorized as a medical field major, and zero otherwise.	Ministry of Education of China
Interested_major	A dummy variable that equals one if the major is categorized as the interested field of major, and zero otherwise.	Ministry of Education of China
I_{post}	A dummy variable that equals one if the individual is old enough for primary school at the time of SARS outbreak, and zero otherwise.	Authors' calculation
$I_{chinese\_med}$	A dummy variable that equals one if the major is a traditional medicine major, and zero otherwise.	Ministry of Education of China
I_{1st_tier}	A dummy variable that equals one if the college is a first-tier college, and zero otherwise.	Ministry of Education of China
Chin_grade	The grade of the surveyed child’s latest Chinese subject examination.	CFPS
SARS_news	Number of newspaper articles on SARS (in hundred) of the surveyed child’s home province in 2003.	China Core Newspapers Full-text Database
Parent med-occupation aspiration	A dummy variable that equals one if the surveyed father/mother hopes his/her child will choose a medical profession, and zero otherwise.	CFPS
Child med-occupation aspiration	A dummy variable that equals one if the surveyed child chooses a medical profession as occupational aspiration, and zero otherwise.	CFPS
Parent_gender	A dummy variable that equals one if the surveyed parent is the father, and zero otherwise.	CFPS
Urban	A dummy variable that equals one if the respondent's lived in an urban area, and zero otherwise.	CFPS

Child_age	Age of the individual surveyed child.	CFPS
Boy	A dummy variable that equals one if the surveyed child is a boy, and zero otherwise.	CFPS
Parent_age	Age of the individual surveyed parents.	CFPS
Parent_educ	An ordered variable that represent the parent's education level: 1 (nonliterate), 2 (elementary school level), 3 (junior high school level), 4 (secondary school/technical secondary school level), 5 (college level), 6 (bachelor's degree), 7 (master's degree), and 8 (doctoral degree).	CFPS
Parent_income	Income of the individual surveyed parent in Yuan.	CFPS
Highest_educ	An ordered variable that represents the highest of the parent's education level: 1 (nonliterate), 2 (elementary school level), 3 (junior high school level), 4 (secondary school/technical secondary school level), 5 (college level), 6 (bachelor's degree), 7 (masters' degree), and 8 (doctoral degree).	CFPS
Household_income	Total household income of the surveyed child's family in Yuan.	CFPS

Note: This table summarizes the definition and source of all variables in our study.

Table A2: Summary statistics

Variables	Mean	Std. Dev.	Min	Max
Panel A: College Major Entry Grade & SARS Impact Data				
AEG percentile rank	46.18	26.7	0	100
Admin_quota	6.65	13.36	0	66
Case	126.12	380.28	0	2434
Case_pc	0.04	0.14	0	1
Med_case	23.24	73.98	0	394
Med_case_pc	0.01	0.02	0	0
Death	6.58	19.7	0	147
Death_pc	0.00	0.01	0	0
Outstanding_ind	8.39	5.24	1	29
Outstanding_ind_pc	0.00	0.00	0	0
Outstanding_inst	2.74	1.87	1	10
Outstanding_inst_pc	0.00	0.00	0	0
Home college	0.09	0.29	0	1
Enroll_quota	356098.1	202603.7	38000	959000
Resident_numer	5015.11	2660.89	554	10999
Medinst_home	35142.96	22926.44	1582	81403
Medinst_growth_home	0.22	0.79	0	5
Medinst_college	36804.46	22146.07	1326	81403
Medinst_growth_college	0.19	0.68	0	5
Licdoc_home	19.93	5.38	10	59
Licdoc_growth_home	0.05	0.10	0	1
Licdoc_college	21.33	5.79	10	59
Licdoc_growth_college	0.04	0.1	0	1
GDP	20366.99	15793.07	1019	80855
GDPPC_home	45313.22	20962.40	9855	118198
Panel B: Children & Parent's Occupational Aspiration Data				
Boy	0.49	0.50	0	1
Urban	0.40	0.49	0	1
Child_age	12.64	1.72	10	15
Parent_educ	1.17	1.32	0	7
Parent_income	10274.93	13832.73	0	180000
Parent_gender	0.46	0.50	0	1
Household_income	12711.9	17983.96	0	200000
Highest_educ	2.70	1.23	1	7

Note: This table provides summary statistics of our major variables. Panel A reported that of the college major entry grade and SARS impact data. SARS impacts are reported both in absolute terms and relative terms, and *AEG percentile rank* is the entry grade's percentile of a major in a college within the target province. Other controls include admission quota (*Admin_quota*), which is minorized at 1% level, whether the target province and college's location is the same (*Enroll Quota*), population of the province (*Resident_number*), medical resources in the target and college's province and their growth rate, and the GDP of the target and college's provinces. Panel B reported that of the Children and parent's occupational aspiration data, where *Boy* is a dummy that equals 1 if the child is a male, and *Urban* is a dummy equals 1 when the participant resident in a urban area. Both *Parent_educ* and *Household_educ* measures the parent's highest education level, while the former is in the children survey and the latter is in the adult survey. Detailed description and construction of the variables can be found in Table A1.

Table A3: SARS impact and medical majors' AEG percentile rank using population-scaled measures

	(1)	(2)	(3)	(4)	(5)
Dependent variable			*AEG Percentile Rank* (%)		
Case_pc	-19.65***				
	(2.565)				
Death_pc		-84.69***			
		(11.52)			
Med_case_pc			-197.6***		
			(28.87)		
Outstanding_ind_pc				-617.0***	
				(89.41)	
Outstanding_inst_pc					-2219.3***
					(307.9)
College clustered	YES	YES	YES	YES	YES
Other controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
College FE	YES	YES	YES	YES	YES
Major FE	YES	YES	YES	YES	YES
Observations	76457	76457	76457	76457	76457
R^2	0.797	0.797	0.797	0.798	0.798

Note: This table presents the analysis of the impact of SARS on the popularity of medical majors using the 2008-2016 sample and population-scaled measures of SARS intensity. The dependent variable is college majors' AEG percentile rank. Population-scaled SARS measure is the log number of absolute SARS measure in the student's (respondent's) home province divided by the population of the province (in 10 thousand), which is population-scaled SARS measure = ln(1+ absolute SARS measure/population). For example, *case_pc* equals ln(1+ cases/population). All regressions are controlled for college, major, and year fixed effects. Definitions for all the variables are provided in Appendix A1. Standard errors are clustered at college level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.